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Review

A Review of Metaheuristic Optimization Techniques for Effective Energy Conservation in Buildings

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Abstract: The built environment is a significant contributor to global energy consumption and greenhouse gas emissions. Advancements in the adoption of environmentally friendly building technology have become crucial in promoting sustainable development. These advancements play a crucial role in conserving energy. The aim is to achieve an optimal design by balancing various interrelated factors. The emergence of innovative techniques to address energy conservation have been witnessed in the built environment. This review examines existing research articles that explore different metaheuristic optimization techniques (MOTs) for energy conservation in buildings. The focus is on evaluating the simplicity and stochastic nature of these optimization techniques. The findings of the review present theoretical and mathematical models for each algorithm and assess their effectiveness in problem solving. A systematic analysis of selected algorithms using MOT is conducted, considering factors that influence wellbeing, occupant health, and indoor environmental quality. The study examines the variations among swarm intelligence MOTs based on complexity, advantages, and disadvantages. The algorithms' performances are based on the concept of uncertainty in consistently providing optimal solutions. The paper highlights the application of each technique in achieving energy conservation in buildings.

Keywords: algorithm; green building; swarm intelligence; energy conservation

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1. Introduction

There is increasing concern about energy conservation, especially among building designers and users in the built environment. In recent times, there have been significant advancements in energy conservation methods and optimization techniques, resulting in reduced energy costs [1]. However, the COVID-19 pandemic has had a substantial impact on global energy demand and the operations of buildings in the construction industry [2]. Many construction projects were postponed or halted due to the limited availability of materials, resources, and contracting capacity. Following the return to post COVID-19 normality, the demand for energy is expected to increase, leading to a rise in environmental challenges associated with the built environment [2].

The objective of improving building efficiency has been achieved through the introduction of various innovative design technologies. These technologies specifically aim to enhance wellbeing, occupant health, and indoor environment quality [3]. Energy efficient technologies can be categorized into passive and low energy design, building services, active systems, and operation design, or a combination of these [4]. The implementation of these design technologies primarily focuses on minimizing energy demand and promoting energy efficient management. It is thus imperative to carry out research and examine smart building concepts and controls to facilitate sustainable operations through optimisation algorithms [5–11]. The relationship between these factors can be noted in Figure 1.

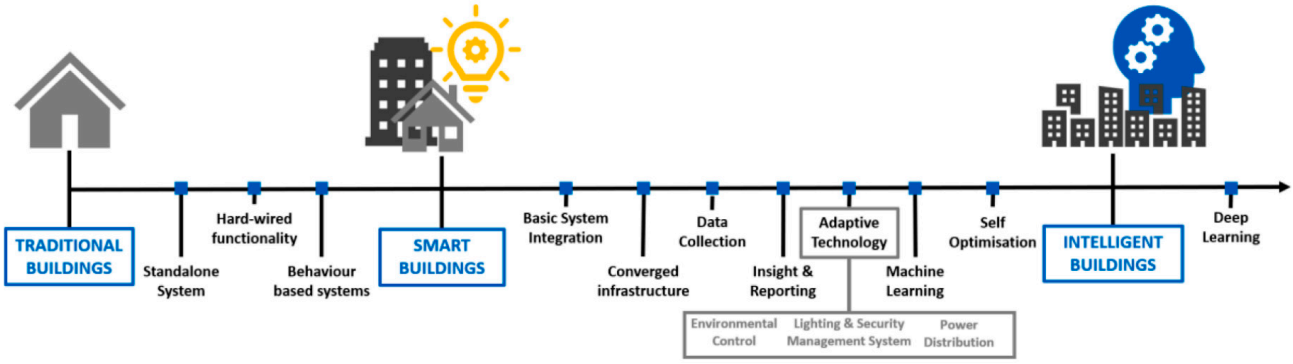


Figure 1. Smart and intelligent buildings through optimization [11].

Implementing green building optimization techniques during the early design stages, particularly in structural planning, presents a significant challenge. These techniques are an integral part of the design process, requiring collaboration between architects, engineers, and others. The formulated approach includes elements in sustainable construction scheduling [2], smart building management and control [4], green building rating tools [12,13], smart power system [14,15], solar energy [16,17], lighting levels [18,19], and greening of roofs [20]. These elements not only ensure compliance with design specifications and regulatory standards, they also contribute to improved occupant health, aesthetics, and overall sustainability.

In 2019, the International Energy Agency (IEA) issued a report [21] showing emissions worldwide attributed to the built environment. It showed that, in 2018, final energy used (36%) and energy and process related CO_2 (39%) constituted the main emissions attributable to the built environment. The report concluded that there had been a 2% increase since 2018, and a 7% increase since 2010, of carbon dioxide emissions. The field of research and technological advancements in energy and environmental systems for buildings is rapidly evolving. This study aims to bridge a gap by offering a comprehensive review of energy and built environment systems, along with relevant optimization techniques. The focus is specifically on smart building systems and their operation [22], encompassing aspects such as smart energy management systems, technologies for optimal functionality and energy efficiency, and the integration of renewable energy applications within smart buildings and their surrounding communities.

In [23], it is highlighted that energy management is a pivotal element in the progression of smart power systems across diverse domains such as microgrids, smart homes, and demand-side management. Nevertheless, the presence of unpredictable variations in renewable energy resources and loads poses significant challenges for energy management due to the associated uncertainty.

By the year 2035, as shown in Figure 2, the annual emissions from newly constructed buildings are projected to be significantly lower than those of existing buildings [21]. This can be achieved by implementing and promoting energy efficient requirements for building construction [13,14]. Retrofitting existing buildings is a global focus for improving energy and water efficiency. However, it is essential to approach retrofitting with caution to avoid ineffective retrofits that may lead to long term maintenance and cost consequences [14]. In [24], the author highlights the importance of prioritizing and meeting regulatory standards with retrofits rather than pursuing inefficient retrofitting, as emphasized by international research findings such as the Advanced Energy Design Guide (AEDG).

The introduction of building norms for new structures represents a positive advancement, supported by the ease of implementation and investment commitment. Although these norms may not be considered groundbreaking compared to current practices [25], there is an expectation for them to become increasingly stringent for new buildings over time [26,27]. The Department of Energy, e.g., in South Africa recognizes the importance of +promoting the development of energy efficient technology markets in addition to focusing

on building materials [25,28]. Their main concern is to encourage advancements in building design and technology to ensure energy efficiency is prioritized.

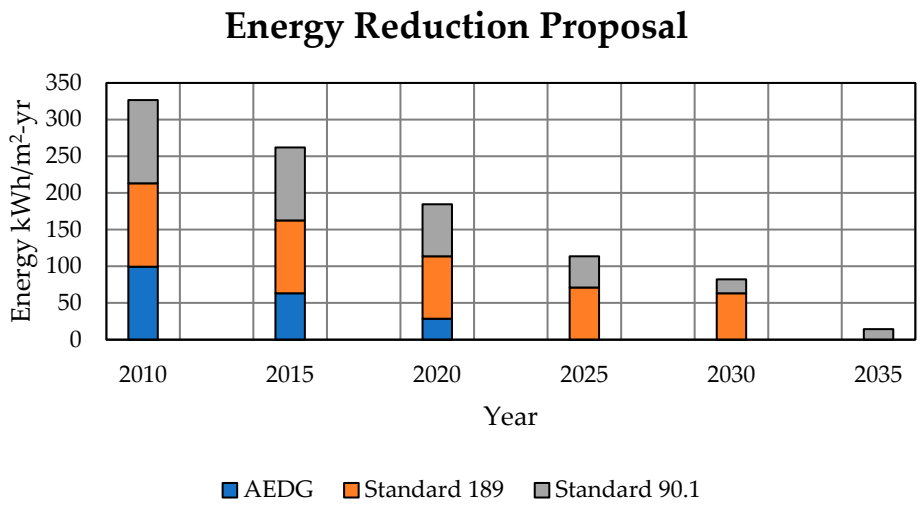


Figure 2. Energy reduction proposals [21].

This study extensively reviews scientific publications that are dedicated to the design, modelling, and optimization of energy and environmental systems, specifically for building applications. The primary focus is on the intelligent management of building energy and environment, as well as strategies to reduce building energy consumption.

The primary objective of this research is to conduct a comprehensive investigation into the impact of employing MOTs for achieving energy conservation. This paper specifically focuses on swarm-based MOTs, examining five distinct techniques. Each technique undergoes a thorough examination, encompassing its inception, mathematical modelling, application process, advantages, disadvantages, and any advancements. The goal is to assess the application of these techniques in the context of energy conservation within a building. This paper serves as a valuable resource for researchers interested in the domain of energy management for buildings.

Following a detailed exposition of each algorithm's structure, the paper delves into an analysis of their respective merits, drawbacks, and evolutionary developments. This information is directly pertinent to the application of these techniques within a building setting. The synthesis of information regarding algorithm advancements and the practical application of swarm-based MOTs to buildings equips researchers with the knowledge needed to effectively leverage specific technique advancements in their pursuit of energy conservation. Consequently, this paper serves as a foundational resource for advancing scientific understanding in the realm of energy conservation and management, contributing to the realization of sustainable, ecofriendly buildings.

While other articles have explored the review of swarm-based MOTs, they often limit their discussion to a subset of algorithms only. Furthermore, a comprehensive review of the impact of advancements in conventional algorithms is notably absent in the existing literature. A comprehensive review focusing on the utilization of swarm-based MOTs for energy conservation in building applications is lacking, which is the primary emphasis of this paper. This work critically assesses and analyses both the advancements in conventional algorithms and their practical application in the context of energy conservation within buildings, filling a significant gap in the current body of research. The paper is organized into the following sections: Section 1 provides an overview of the research paper. Section 2 explains the methodology employed for conducting the literature review. Section 3 delves into the specific scope of work and design specifications considered in the study. Section 4 discusses various optimization techniques in green buildings, drawing from relevant research papers. Section 5 highlights the main findings and discussion on the

MOTs explored for simulation. Section 6 presents conclusions drawn from the research. Additionally, recommendations for further research are provided in Section 6.

By structuring the paper in this manner, as in Figure 3, the authors aim to present a comprehensive analysis of optimization techniques in green buildings, culminating in key insights and suggestions for future research. The main contributions of this paper are as follows:

1. Provide an in depth review of the operational principles governing five swarm-based metaheuristic optimization techniques (MOTs). This includes presenting the fundamental equations essential for the implementation of each algorithm accompanied by visual flow charts delineating the stepwise process for their effective application.
2. Conduct a comprehensive assessment of the advantages and drawbacks associated with each algorithm, followed by an examination of recent developments aimed at addressing and mitigating the identified shortcomings.
3. Evaluate the application of these algorithms in the realm of achieving energy conservation in building environments. This analysis entails identifying any existing gaps or deficiencies within the current literature specific to this application.
4. Undertake a comparative review distinguishing between "good" and "better" optimization algorithms tailored for simulation, particularly focusing on specific zones that necessitate optimized dynamic designs during the early stages.

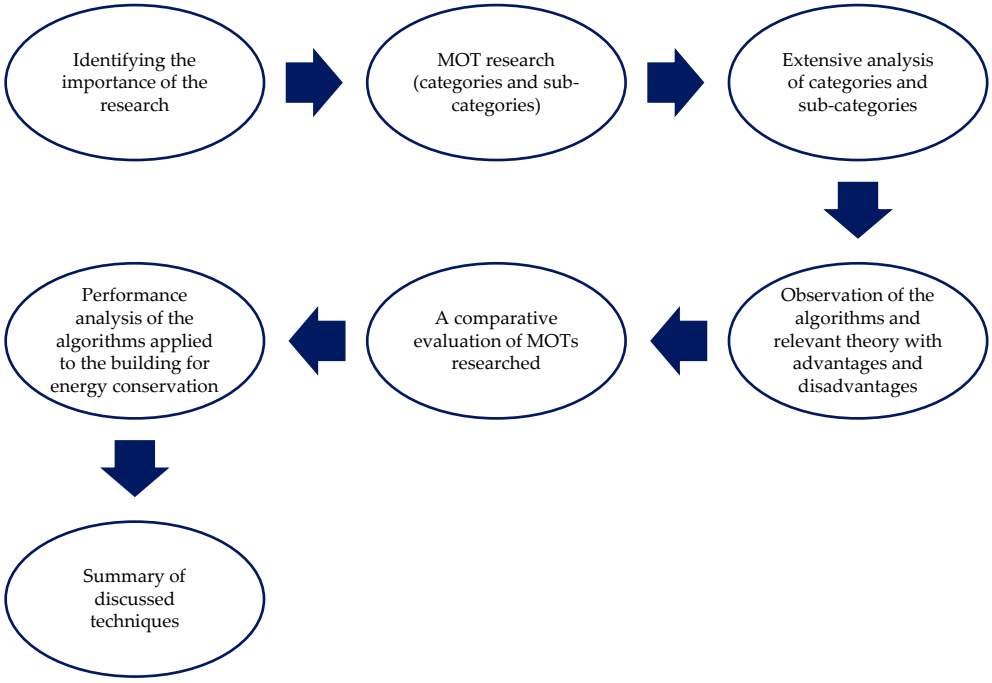


Figure 3. Flow process of methodology employed.

2. An Overview of Energy Conservation in Buildings

The preservation of energy in buildings is an essential element of sustainable progress and the mitigation of environmental effects [29]. It encompasses the adoption of diverse approaches and technologies aimed at reducing energy usage while ensuring comfortable living or working environments [30]. Energy conservation in green buildings focuses on reducing energy consumption and increasing energy efficiency [31] in environmentally friendly and sustainable building designs [32]. Green buildings prioritize energy efficient systems, renewable energy integration, and sustainable practices [33,34].

Through the utilization of this high level overview, shown in Figure 4, building owners and managers can systematically identify, prioritize, and execute energy conservation measures, ultimately resulting in enhanced energy efficiency and a diminished environmental footprint. The adoption of building standards for new structures represents a significant

and positive development due to their user friendly nature and the commitment they require in terms of investment. While these standards may not be perceived as revolutionary compared to existing practices, there is an expectation that they will become progressively more stringent for new structures as time goes on [35,36]. The South African Department of Energy's primary objective is to promote the advancement of buildings by advocating for energy efficient technology markets. This approach extends beyond a sole focus on a building's materials [37,38].

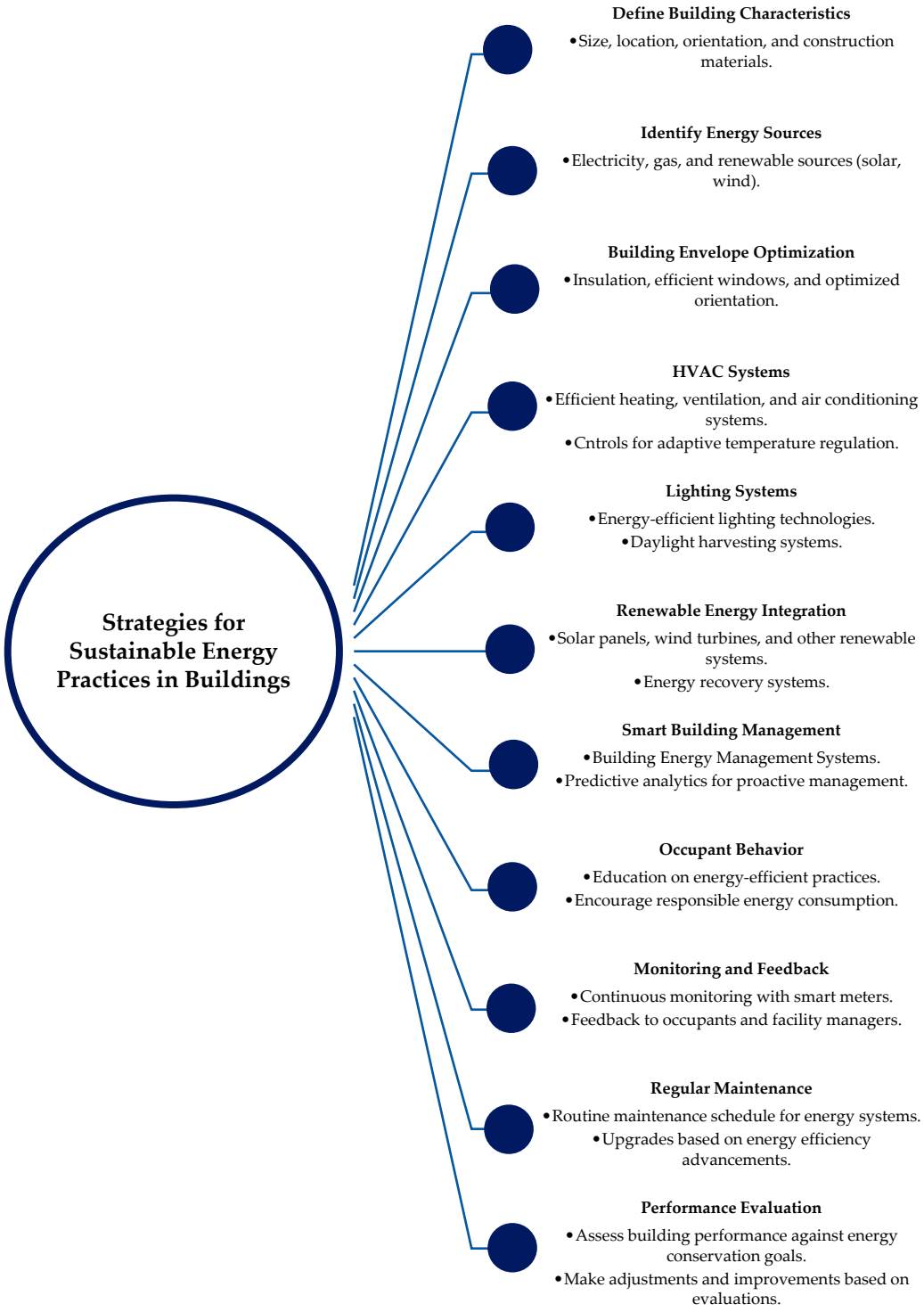


Figure 4. An overview of strategies for sustainable energy practices in buildings [33].

The primary hurdle to enhancing energy efficiency within the public sector lies in retrofitting existing buildings [35,37]. The focus of the proposed methods, therefore, is on identifying approaches to renovate public structures, while also considering limited funding from the public sector and the utilization of innovative financing mechanisms, as follows:

1. Sustainable constructions incorporate passive design approaches to optimize natural lighting, enhance thermal insulation, and maximize solar heat gain [31]. These strategies encompass efficient building orientation, shading mechanisms, high performance windows, and well insulated building envelopes [32,34].
2. Environmentally conscious buildings employ energy efficient heating, ventilation, and air conditioning (HVAC) systems [32]. This includes utilizing high efficiency equipment such as variable refrigerant flow (VRF) systems, heat pumps, and energy recovery ventilation (ERV) systems [31,36]. Advanced control systems and zoned heating and cooling contribute to the optimization of HVAC energy consumption [35].
3. Green buildings often integrate renewable energy technologies to generate clean power on site [32]. Solar photovoltaic (PV) panels, wind turbines, and geothermal systems are commonly employed to offset electricity consumption and minimize reliance on conventional energy sources [31,36].
4. Smart energy management systems are implemented to monitor, control, and optimize energy usage within green buildings [33]. These systems utilize sensors, data analytics, and automation to ensure the efficient operation of building systems, such as lighting, HVAC, and plug loads [33,36].
5. Environmentally friendly buildings utilize energy efficient lighting solutions, such as LED fixtures, intelligent lighting controls, and occupancy sensors [34,36]. Daylighting strategies are also employed to maximize the utilization of natural light and minimize the need for artificial lighting [35].
6. Continuous monitoring and benchmarking of energy performance enable green buildings to identify areas for improvement and ensure the achievement of energy conservation objectives [31]. Energy management systems and monitoring tools provide real-time data for analysis and informed decision making [33,36].
7. Building automation and control systems (BACS) offer centralized control and automation for diverse building systems [32]. These systems facilitate real-time monitoring, remote control, and advanced energy management, leading to enhanced energy efficiency and operational performance [34].

3. Metaheuristic Optimization Techniques

As the name implies, metaheuristic optimization techniques (MOTs) are control techniques that are not specific to any problem domain. Metaheuristic techniques are valued for their simplicity, flexibility, and proficiency in efficiently addressing complex problems. These methods heavily rely on the utilization of randomness with the objective of discovering optimal solutions through a combination of diversification and intensification. Diversification involves conducting a broad search across the entire solution space, exploring various possibilities. Intensification, on the other hand, focuses on refining the search by concentrating on promising regions within the solution space. By striking a balance between exploration and exploitation, metaheuristic techniques aim to efficiently converge towards optimal solutions.

MOTs draw inspiration from diverse aspects of daily life, encompassing the human body, the laws of physics, and animal behavior in natural environments [39]. Through the critical evaluation of the operational mechanisms within these realms, precise mathematical models have been developed to simulate natural phenomena effectively. Subsequently, these models have been successfully applied to address complex engineering problems with optimal outcomes. Although no definitive categorization of MOTs exists, they are typically classified into four main categories, each offering unique approaches and advantages to

problem solving. The classification shown is not an extensive list of MOTs but accounts for the most recent methods implemented.

The four categories of the classification are tabulated in Tables 1–4, below, highlighting each of the algorithms and its examples together with its year of emergence [39].

Table 1 shows the examples of evolution-based algorithms, where algorithms are inspired by natural evolution.

Table 2 shows the examples of swarm intelligence algorithms, where algorithms are inspired by the behavior of animals, insects, fish, birds, and bacteria.

Table 3 shows the examples of physics-based algorithms, where algorithms are inspired by physical science and chemical occurrences.

Table 4 shows the examples of human related algorithms, where algorithms are inspired by the behavior of human beings.

Table 1. Classification of evolution-based MOTs researched [39].

Metaheuristic Optimization Techniques		
Evolution Based Algorithms	**Abbreviation**	**Year**
Evolutionary programming	EP	1966
Evolution strategy	ES	1973
Genetic algorithm	GA	1975
Tabu search	TS	1986
Differential evolution	DE	1997
Differential search algorithm	DS	2011
Synergistic fibroblast optimization	SFO	2019
Physarum-inspired computational model	PCM	2020

Table 2. Classification of swarm intelligence MOTs researched [39].

Metaheuristic Optimization Techniques		
Swarm Intelligence Algorithms	**Abbreviation**	**Year**
Ant colony optimization	ACO	1992
Particle swarm optimization	PSO	1995
Artificial fish swarm algorithm	AFSA	2002
Bacteria foraging optimization algorithm	BFOA	2002
Glow worm swarm optimization		2005
Cat swarm optimization	CSA	2006
Artificial bee colony optimization	ABC	2007
Cuckoo search	CS	2009
Bat algorithm	BA	2010
Firefly algorithm	FA	2010
Krill herd algorithm	KH	2012
Dolphin echolocation		2013
Chicken swarm optimization	CSO	2014
Grey Wolf optimization	GWO	2014
Ant lion optimization	ALO	2015
Dragonfly algorithm	DA	2015
Whale optimization algorithm	WOA	2016
Grasshopper optimization algorithm	GOA	2017
Butterfly inspired algorithm	BOA	2017
Salp swarm algorithm	SSA	2017
Equilibrium optimizer	EO	2019
Bald eagle search	BES	2019
Harris hawks optimization	HHO	2019
Nuclear reaction optimization	NRO	2019
Slime mold algorithm	SMA	2020
Border collie optimization	BCO	2020

Table 3. Classification of physics-based MOTs researched [39].

Metaheuristic Optimization Techniques		
Physics Based Algorithms	**Abbreviation**	**Year**
Simulated annealing	SA	1983
Harmony search	HS	2001
Big bang–big crunch optimization	BBCB	2005
River formation dynamics	RFD	2007
Gravitational search algorithm	GSA	2009
Ray optimization	RO	2012
Mine blast algorithm	MBA	2013
Lightning search algorithm	LSA	2015
Sine cosine algorithm	SCA	2016
Multiverse optimization algorithm	MVO	2016
Thermal exchange optimization	TEO	2017
Henry gas solubility optimization	HGSO	2019

Table 4. Classification of human related MOTs researched [39].

Metaheuristic Optimization Techniques		
Human Related Algorithms	**Abbreviation**	**Year**
Human inspired algorithm	HIA	2009
Social emotional optimization	SEOA	2010
Brain storm optimization	BSO	2011
Teaching–learning based optimization	TLBO	2011
Volleyball premier league algorithm	VPL	2018
Gaining sharing knowledge	GSK	2019

The application of MOTs has been extensively explored in the renewable energy systems field. In [39], a survey was conducted on the use of metaheuristic optimization techniques and its various applications were examined. In [40] the article encompassed techniques of metaheuristic optimization from four categories, both in their conventional and modified forms, resulting in a comprehensive analysis. The study in [41] considered techniques from all four categories of metaheuristic optimization, both in their predictable and improved versions. In addition [42], a comprehensive survey was conducted to assess the impact of gas solubility and bat algorithm techniques. The survey examined seven categories of algorithm, including metaheuristic optimization techniques as one of the categories. Within this category, three out of the four subcategories of metaheuristic optimization were discussed.

In essence, this paper aspires to be a valuable and all-encompassing resource. By not only offering an overview of swarm-based MOTs, but also concentrating specifically on their practical deployment for achieving energy conservation in building environments, the paper endeavours to be instructive for researchers, practitioners, and stakeholders involved in the domain of energy efficient building design.

4. Review and Summary of Swarm Intelligence Algorithms

Building energy optimization using swarm intelligence algorithms is a powerful approach to design and operate more energy efficient, sustainable, and cost effective buildings. These design algorithms help to reduce energy consumption, lower operational costs, and minimize environmental impact while providing a comfortable and healthy indoor environment for occupants [43].

The key steps and aspects of building energy optimization using swarm intelligence algorithms are as follows [44,45]:

1. Defining an objective function that quantifies the energy consumption or related performance metrics (e.g., cost, emissions, etc.) of the building. This function represents the optimization goal.

2. Identifying the parameters and variables that can be adjusted to optimize building energy consumption. These parameters include HVAC settings, lighting levels, insulation materials, and window properties.
3. Defining the constraints that ensure the optimization process respects comfort and safety standards. Constraints include temperature limits, humidity levels, and lighting requirements.
4. Creating a building energy simulation model that predicts how changes in the parameters affect energy consumption. This model is used to evaluate potential solutions generated by the optimization algorithm.
5. Choosing an optimization algorithm suitable for the problem, e.g., genetic algorithms, particle swarm optimization, artificial bee colony optimization, etc.
6. Initializing a population of potential solutions or candidate parameter values. The initial solutions are generated randomly and based on existing building conditions.
7. Evaluating the fitness of each potential solution using the objective function and the building energy model. Solutions that minimize energy consumption and satisfy constraints are considered better solutions.
8. Applying the chosen optimization algorithm to iteratively search for better solutions by modifying the parameters. The algorithm explores the solution space to find optimal configurations.
9. Defining the stopping criteria for the optimization process, such as a maximum number of iterations or a minimum improvement threshold. This prevents excessive computational time.
10. Applying the best solution found by the algorithm to the real building system. This could involve adjusting building parameters, scheduling energy saving measures, or implementing energy efficient technologies.
11. Continuously monitoring the building's energy consumption to ensure that the optimized parameters and strategies remain effective. Periodic maintenance and re-optimization may be necessary to adapt to changing conditions and occupant behavior.
12. Using real-time data and feedback mechanisms to adapt the building's operation in response to changing conditions, occupancy patterns, and energy prices.

The objective function for quantifying the energy consumption of a building involves defining a mathematical expression that integrates various factors influencing energy usage. In the context of building energy consumption, contributors include heating, cooling, lighting, and equipment energy use [46]. The objective function aims to represent the overall energy performance of the building. The steps highlighting energy consumption can be defined by the equation below [46], where H is the energy used for heating, C is the energy used for cooling, L is the energy used for lighting, E is the energy used by equipment, and T is the total energy consumption. The objective function F can be expressed as a weighted sum of these components [46]:

$$F(H,\ C,\ L,\ E) = \omega_H \cdot H + \omega_C \cdot C + \omega_L \cdot L + \omega_E \cdot E + \omega_T \cdot T \quad (1)$$

where, ω_H, ω_C, ω_L, ω_E, and ω_T are weighted factors representing the relative importance of each component in the overall energy consumption. The weights are determined based on the significance of each factor in the context of the building's energy profile. The objective function serves as a basis for optimization algorithms, such as MOTs, to find the optimal combination of building parameters that minimizes energy consumption. The objective function encapsulates the holistic energy usage scenario, offering a quantitative measure that optimization algorithms can aim to minimize [47].

Optimizing building energy usage is certainly a critical aspect of sustainable construction. Swarm intelligence algorithms, which draw inspiration from the collective behavior of social organisms, are employed to improve the energy efficiency of buildings. These algorithms iteratively explore and adjust parameters to find optimal solutions, contributing to the overall sustainability and performance of structures. These algorithms combine

building parameters and control strategies to minimize energy consumption while maintaining or improving occupant comfort [48]. This section of the paper reviews the various swarm intelligence algorithms. The techniques to be discussed include particle swarm optimization, artificial bee colony optimization, cuckoo search optimization, bat algorithm, and firefly optimization. Each technique undergoes scrutiny with respect to its motivation, structural characteristics, strengths, weaknesses, recent improvements, and its specific application within the realm of energy conservation and management in buildings.

4.1. Particle Swarm Optimization

Taking inspiration from the collective behavior observed in schooling fish and flocking birds, particle swarm optimization (PSO) is an MOT that was jointly developed by an electrical engineer and a social psychologist [49]. In PSO, a population of particles is employed, and these particles move with specific velocities. The velocity of each particle is continuously reviewed after each iteration, considering various influencing factors. PSO is inspired by the social behavior of birds and fish and is widely used in optimization problems to find optimal solutions by iteratively adjusting the velocities of these particles. PSO's control algorithm is simple in that it imposes a small computational burden [49–54]. The position of a particle is established based on its prior location and its current velocity. The expression is represented as [49,52,53]:

$$\overline{x}_i(t+1) = \overline{x}_i(t) + \overline{v}_i(t) \tag{2}$$

where $\overline{x}_i(t+1)$ represents the particles updated position, $\overline{x}_i(t)$ denotes the particles current position, and $\overline{v}_i(t)$ represents the particle's current velocity. The current velocity of the system is defined as [49,52,53]:

$$\overline{v}_i(t+1) = \overline{v}_i(t) + \sigma_1 \times rand1 \times (\overline{p}_i - \overline{x}_i(t)) + \sigma_2 \times rand2 \times \left(\overline{p}_g - \overline{x}_i(t)\right) \tag{3}$$

where $\overline{v}_i(t+1)$ represents the updated velocity of the particle at time, σ_1 and σ_2 are two positive numbers, $rand1$ and $rand2$ are two randomly generated numbers in the range [0, 1], $\overline{p}_i$ represents the individual best of each particle, and $\overline{p}_g$ represents the global best among all particles. Equation (3) comprises three integral components. The first term reflects the particle's inertia adhering to Newton's first law, which asserts that an object in motion tends to remain in motion unless an external force is applied [54]. The second term signifies the particle's inclination to converge toward its individual best solution. The third term indicates the particle's inclination to gravitate toward the globally best solution, recognized as the social component [49,50]. To ensure convergence and prevent divergence, it is important to set appropriate constants and limitations. One critical limitation is the maximum velocity, which needs to be properly selected. An excessively high maximum velocity can result in unstable behavior, while an overly low velocity constraint can restrict the search space and potentially impede the discovery of the most optimal solution. Research conducted in [51] illustrates that dynamically adjusting the maximum velocity can improve the algorithm's overall performance. Another important limitation is the acceleration constants' values, σ_1 and σ_2. Studies in [53,54] showed that if the sum of σ_1 and σ_2 exceeds 4, the particle trajectories may diverge (go to infinity). The acceleration constants' values can be dynamically updated by calculating them with reference to a range between a maximum and minimum value, in addition to considering the current and maximum iteration number [55].

To mitigate the potential problem of particle divergence, there are two methods that can be employed in the context of Equation (3). The first method entails the use of a constant referred to as the constriction factor, which is applied to the entire equation and is determined based on the acceleration constants [53]. The second method involves the application of a fixed or dynamically adjusted value to the inertia component within Equation (3) [53]. This is the constant inertia value, and it typically commences with a high value, gradually diminishing over time. In the case of a dynamic inertia constant, denoted

as w, inertia weights are typically computed utilizing an initial weight (commonly set to 0.9), a final weight (typically set to 0.4), and considering the current iteration number as well as the maximum iteration number [53]. The judicious choice of inertia weights can result in fewer iterations being required to achieve a satisfactory solution [54].

A visual representation of the steps involved in executing the PSO can be found in Figure 5 [56]. When applied to building energy conservation, PSO can help find energy efficient configurations and strategies. PSO is used in this context, as follows [57,58]:

1. Define an objective function that quantifies the energy consumption of the building. This function considers various factors, such as heating, cooling, lighting, and equipment energy use.
2. Identify the parameters that can be optimized to conserve energy in the building. These parameters include thermostat settings, HVAC system operation schedules, insulation levels, renewable energy integration, and the use of energy efficient appliances and lighting.
3. Define constraints that ensure occupant comfort and building performance. These constraints include temperature and humidity limits, lighting levels, and indoor air quality standards.
4. Develop a building energy simulation model that predicts how changes in the parameters affect energy consumption. This model serves as the basis for evaluating solutions generated by the PSO algorithm.
5. Initialize a population of particles with potential solutions. Each particle represents a different combination of parameter values, which are candidates for optimizing energy conservation.
6. Apply PSO rules to update the velocity and position of each particle in the swarm. Particles adjust their positions based on their own experience and the collective experience of the swarm.
7. Evaluate the fitness of each particle using the objective function and the building energy model. Particles with lower energy consumption values have better fitness.
8. Keep track of the best positions (solutions) found by each particle individually (best personal positions) and across the entire swarm (best global positions).
9. Determine the convergence criteria, such as a maximum number of iterations, a minimum improvement threshold, or a specific time frame, to stop the optimization process.
10. Apply the best solution found by PSO to the real building system. This involves adjusting building parameters, optimizing scheduling, or introducing energy efficient technologies and practices.
11. Continuously monitor the building's energy consumption to ensure that the optimized parameters and strategies remain effective. Periodic maintenance and re-optimization may be necessary to adapt to changing conditions and occupant behavior.

PSO emerges as an innovative and robust methodology for revolutionizing building energy conservation, introducing a dynamic and adaptive approach to discovering optimal solutions that harmoniously balance energy efficiency, occupant comfort, and operational requirements [59]. At the core of this innovation is the simulation of a swarm of particles within the parameter space, with each particle representing a potential solution [60]. This deep-thinking strategy involves particles navigating the solution space and continually adjusting their positions based on individual experiences and the collective wisdom of their neighbors. In building energy conservation, where the aim is to optimize parameters such as thermostat settings, HVAC system schedules, and other influential factors on energy consumption [61], PSO's adaptability shines. The adaptive nature of PSO enables it to effectively respond to real-world changes in building conditions, encompassing variations in occupancy, weather, or equipment efficiency [62]. This deep-thinking adaptability becomes crucial in scenarios where dynamic building conditions cannot be precisely predicted. PSO's iterative nature facilitates efficient exploration of the solution space, converging towards optimal configurations. The innovative fusion of data-driven optimization and adaptability aligns seamlessly with broader sustainability goals, making PSO a powerful

tool for promoting energy efficient practices and sustainability in building operations [63]. In a fusion of ideas, PSO not only aims to minimize energy consumption but also respects constraints related to occupant comfort, indoor air quality, and operational requirements. This fusion approach involves integrating PSO with smart technologies, sensor networks, or advanced control strategies, deepening its adaptability and effectiveness in handling complex building systems [64]. The application of PSO in building energy conservation reflects a forward thinking strategy, contributing significantly to the long term environmental and economic sustainability of buildings and urban infrastructure. By embracing innovation, deep thinking, and fusion, PSO stands as a cornerstone in the pursuit of energy efficient and sustainable building practices.

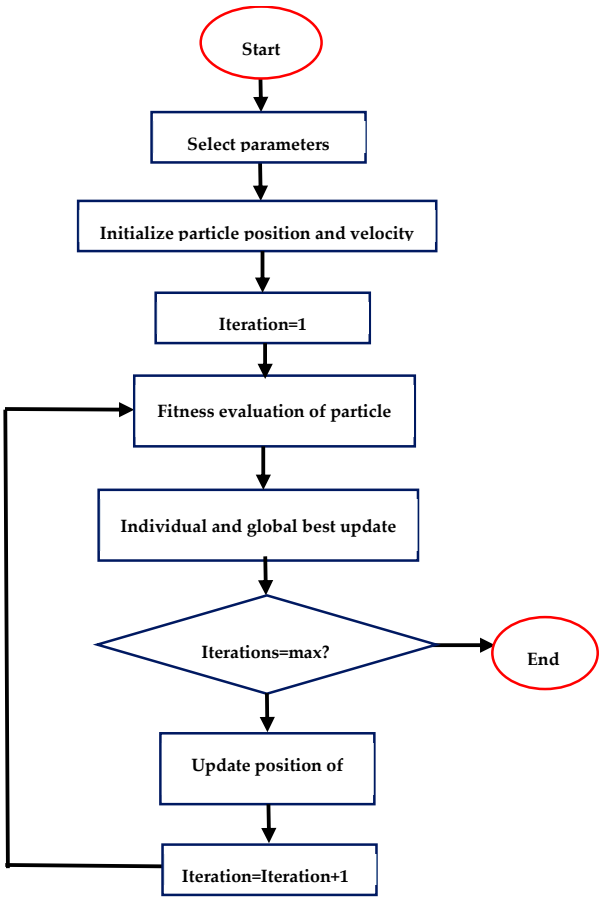


Figure 5. Particle swarm optimization (PSO) algorithm flowchart [56].

4.2. Artifical Bee Colony Optimization

The artificial bee colony (ABC) algorithm is a metaheuristic optimization technique inspired by the hunting behavior of honeybees. Developed by Karaboga, this algorithm emulates the division of labour seen in a beehive, which involves three distinct roles: employed bees, onlooker bees, and scout bees [65–67]. Employed bees are actively engaged in exploiting a food source they have discovered. In contrast, onlooker bees observe and await information gathered by employed bees to make decisions. The scout bee, as its name suggests, is responsible for autonomously and randomly seeking out new food sources [66,67]. Each food source is initially assigned to an employed bee. However, when a food source becomes depleted, either due to another employed bee or an onlooker bee, the previously employed bee transforms into a scout bee and commences the quest for new food sources [67]. Communication of information about food sources occurs through a dance performed by the employed bees. The onlooker bees observe these dances to gather information and choose the best quality food source to exploit [67]. The hunting behavior of the bees, referred to as foraging, is characterized by four main aspects [68–70]:

1. Positive feedback: when an employed bee discovers a high quality food source, it performs a dance to communicate this information to the onlooker bees. The onlooker bees are then attracted to the rich food source, resulting in an increased number of visits to that source.
2. Negative feedback: if an employed bee finds a food source that is of low quality or depleted, it becomes a scout bee and starts searching for new food sources. This behavior prevents the bees from wasting time and resources on unproductive or suboptimal sources.
3. Fluctuations: scout bees explore the search space in a random manner, allowing for exploration of new regions. This random exploration introduces variability into the algorithm and helps avoid getting stuck in local optima.
4. Multiple interactions: employed bees communicate the quality and location of food sources through their dances, and onlooker bees observe and evaluate these dances to determine the best food source to exploit. This exchange of information facilitates cooperative behavior among the bees and helps in the overall optimization process.

The population size is determined by the number of food sources, and each food source represents a potential solution to the problem being solved. The quality of a food source corresponds to the fitness of the solution it represents [66,67]. The population consists of multiple solutions, with each food source associated with an employed bee or a scout bee. Initially, the scout bees randomly choose their food source, and the scouts become employed bees when they discover a food source [68]. The employed bees embark on searching for additional food sources located near their current one. They assess the quality of these nearby potential food sources through visual representation. Utilizing a greedy selection process, a newly discovered food source proves to be of superior quality compared to the one previously known to the employed bee [69].

Onlooker bees receive information from the employed bees through the dancing area, which indicates the quality of the food sources. Based on the received information and probabilities (such as the roulette wheel method), onlooker bees select a food source to visit and search for other potential food sources nearby. The greedy selection is again applied to compare the new and previous food sources [67,70]. Should an employed bee's food source not exhibit improvement after a certain number of attempts, the employed bee undergoes a transformation into a scout bee. It abandons its current food source and initiates a random search for a new one [68,69]. This process continues until a specified termination criterion is satisfied, as seen in Figure 6 [70], which could be a maximum number of iterations, reaching a certain fitness threshold, or other criteria specific to the problem being solved. This can be represented as [67]:

$$x_{i,j} = [\, x_{1,1}, x_{1,2} \ldots x_{S,D}], \; i \in [1, 2, 3 \ldots S] \text{ and } j \; \in [1, 2, 3 \ldots D] \tag{4}$$

Here, "S" represents the population size, which corresponds to the total number of solutions, and "D" is the number of parameters to be optimized. The employed bee's initial position is depicted as follows [67,68]:

$$x_{0,i,j} = x_{j\ min} + \Phi_{ij}\left(x_{j\ max} - x_{j\ min}\right) \tag{5}$$

A visual representation of the steps involved in executing ABC can be found in Figure 6 [70]. When applied to building energy conservation to find optimal solutions for reducing energy consumption and improving sustainability, ABC mimics the foraging behavior of honeybees to search for the best solutions within a search space. ABC is applied in the context of building energy conservation, as follows [71,72]:

1. Define an objective function that quantifies the energy consumption of the building. This function considers factors such as heating, cooling, lighting, and equipment energy use.
2. Identify the parameters that can be optimized to enhance energy conservation in the building. These parameters include thermostat settings, HVAC system operation

schedules, insulation levels, renewable energy integration, and the use of energy efficient appliances and lighting.

3. Define the constraints to ensure occupant comfort and building performance. These constraints include temperature and humidity limits, lighting levels, indoor air quality standards, and cost constraints.
4. Develop a building energy simulation model that predicts how changes in the parameters affect energy consumption. This model is used to evaluate the solutions generated by the ABC algorithm.
5. Initialize a population of artificial bees, each representing a different combination of parameter values. These bees explore the search space for optimal solutions.
6. The artificial bees scout the solution space, evaluate potential solutions, and communicate their findings to other bees in the colony. Successful solutions are communicated more frequently, while poor solutions are less frequently communicated.
7. Evaluate the fitness of each bee (solution) using the objective function and the building energy model. Bees with lower energy consumption values have higher fitness.
8. Maintain records of the best solutions found by individual bees and the entire colony throughout the optimization process.
9. Determine the convergence criteria, such as a maximum number of iterations or a minimum improvement threshold, to stop the optimization process.
10. Apply the best solution found by ABC to the real building system. This may involve adjusting building parameters, optimizing scheduling, or introducing energy efficient technologies and practices.
11. Continuously monitor the building's energy consumption to ensure that the optimized parameters and strategies remain effective. Periodic maintenance and re-optimization may be necessary to adapt to changing conditions and occupant behavior.

In the realm of building energy conservation, the utilization of ABC optimization introduces innovative and impactful advantages, fostering energy optimization while ensuring occupant comfort and operational efficiency [73]. Similarly to PSO, ABC exhibits a global exploration capability, efficiently traversing a broad solution space [74]. This innovation is paramount in navigating the intricate domain of building energy conservation, where finding optimal or near-optimal solutions is inherently complex. Deep thinking is embedded in ABC's dynamic adaptability to changing conditions, aligning seamlessly with the dynamic nature of building environments. The deep-thinking approach acknowledges the fluctuations in occupancy, external temperatures, and other factors, allowing ABC to dynamically adjust its solutions to meet evolving needs [75]. Mirroring PSO, ABC strikes a delicate balance between exploration (searching for new solutions) and exploitation (refining existing solutions), a crucial aspect for discovering novel energy efficient strategies and refining known ones [76]. Notably, ABC's efficiency in converging to optimal solutions is well suited for the timely decision making demands of building energy conservation, further showcasing its innovative capabilities. In a fusion of concepts, ABC's adaptability extends to effective constraint handling, addressing constraints related to comfort levels, indoor air quality, and other factors inherent in building energy conservation [77]. This fusion strategy involves integrating ABC with smart technologies, constraint satisfaction methods, or advanced control strategies, enhancing its capacity to navigate constrained solution spaces effectively. By optimizing energy consumption, ABC significantly contributes to the long term sustainability of building operations, aligning with green building principles and promoting energy savings with reduced environmental impact [78]. ABC's dynamic adaptation, efficiency, and global exploration capabilities make it a promising tool for building energy conservation. This fusion of innovation, deep thinking, and adaptability positions ABC as a valuable contributor to sustainability and operational efficiency in diverse building contexts [79].

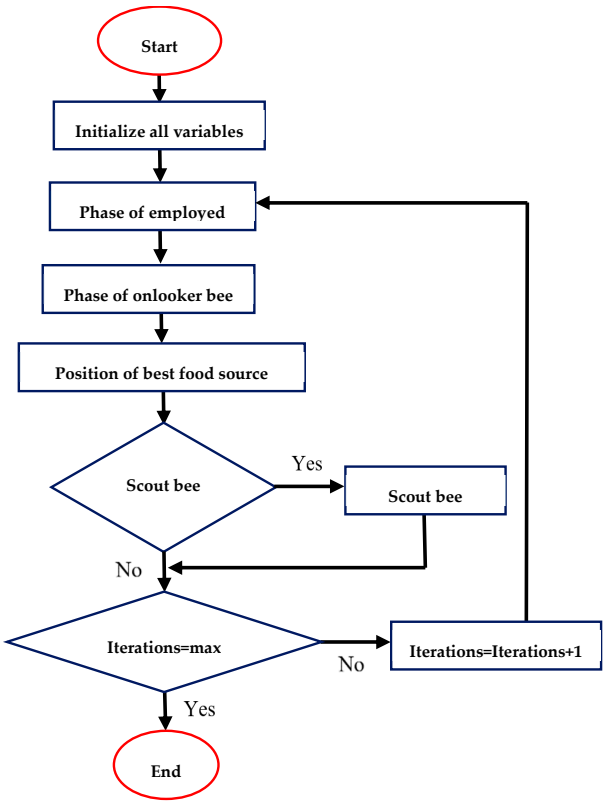


Figure 6. Artificial bee colony optimization (ABC) algorithm flowchart [74].

4.3. Cuckoo Search Algorithm

In the cuckoo search algorithm (CuSA), proposed by Yang and Deb [80,81], the behavior of cuckoo birds is used as inspiration. Cuckoos are parasitic birds that lay their eggs in the nests of other birds. To ensure their eggs are not rejected by the host bird, cuckoos lay eggs that mimic the appearance of the host eggs in terms of shape and colour. Cuckoo eggs often hatch earlier than the host eggs, and, once hatched, the cuckoo chick displaces the host eggs to gain a larger share of food resources [80,81].

The CuSA algorithm follows three rules [80]. Firstly, each cuckoo bird lays only one egg, randomly placing it in a nest. Secondly, the best nest, which contains high-quality eggs resembling the cuckoo eggs, has a higher chance of being shifted to the next generation. This rule emphasizes the selection of nests with better solutions. Thirdly, the number of nests remains constant throughout the algorithm, meaning there is no change in the population size. Additionally, there is a probability that the host bird may discover the cuckoo egg and either abandon it or remove it from the nest, resulting in the egg not surviving. This probabilistic event represents a form of selection pressure within the algorithm.

Where $x_i(t)$ is the current position of the cuckoo, $x_i(t+1)$ is the next position of the cuckoo, α is a randomized number which is usually 1, σ is element-wise multiplication, and λ is a randomized value between 1 and 3, the following procedure is employed to modify the nest's position and for another egg to be laid by a cuckoo [82,83]:

$$x_i{}' = \begin{cases} x_i + r(x_{r1} - x_{r2}), & \text{rand}[0,1] > \text{Pa} \\ x_i, & otherwise \end{cases} \quad (6)$$

where $x_i{}'$ is the updated position of the nest, r and rand [0, 1] are randomized numbers in the range [0, 1], $r1$ and $r2$ are different randomized integers with a maximum to that equal to the number of cuckoos, and Pa is the probability of the host bird identifying and discarding the cuckoo egg and is a randomized number in the range [0, 1].

A visual representation of the steps involved in executing the CuSA can be found in Figure 7 [83]. The steps when applied to building energy conservation and optimization is, as follows [84,85]:

1. Define an objective function that represents the energy consumption of the building. This function considers various factors, including heating, cooling, lighting, and equipment energy use.
2. Identify the parameters that can be adjusted to optimize building energy conservation. These parameters include thermostat settings, HVAC system operation schedules, insulation levels, and the use of energy efficient appliances and lighting.
3. Define constraints, such as comfort limits for indoor temperature, humidity, and lighting levels. These constraints ensure that any optimization achieved by the cuckoo search algorithm maintains occupant comfort.
4. Develop a building energy simulation model that predicts how changes in the parameters affect energy consumption. This model serves as the basis for evaluating solutions generated by the cuckoo search algorithm.
5. Initialize a population of "cuckoo" agents with potential solutions. These agents represent different combinations of parameter values.
6. Evaluate the fitness of each cuckoo agent using the objective function and the building energy model. The fitness function should reflect the energy consumption reduction goal.
7. Cuckoo search employs Levy flights for exploration. Levy flights allow the cuckoos to explore the solution space by moving in a manner that balances exploration and exploitation.
8. Cuckoo search uses egg laying to generate new solutions. This process allows cuckoos to produce new solutions based on the best solutions found so far and replace poor solutions in the population.
9. Determine the convergence criteria, such as a maximum number of iterations or a minimum improvement threshold, to stop the optimization process.
10. Apply the best solution found by the cuckoo search algorithm to the real building system. This could involve adjusting building parameters, scheduling energy saving measures, or implementing energy efficient technologies.
11. Continuously monitor building energy consumption to ensure that the optimized parameters and strategies are effective. Periodic maintenance and re-optimization may be necessary to adapt to changing conditions and occupant behavior.

The CuSA introduces an innovative approach to building energy conservation by maintaining a nuanced equilibrium between global exploration and local exploitation [86]. This innovative strategy reflects deep thinking in its ability to efficiently explore a diverse solution space while strategically refining solutions in promising regions, addressing the intricacies of energy optimization within building systems. CuSA's adaptability to dynamic conditions marks an innovative solution for building energy conservation, enabling the algorithm to dynamically respond to changes in occupancy patterns, weather conditions, or equipment efficiency for ongoing optimization. This adaptability showcases a forward thinking approach to handling the dynamic challenges of building environments [87,88]. CuSA's efficient convergence to optimal solutions aligns with innovation in real-time building energy management, ensuring timely and effective solutions. The parameter customization options provided by CuSA not only allow for adaptability but also demonstrate deep thinking in tailoring the algorithm to suit specific building energy conservation requirements. The fusion strategy involves fine tuning CuSA's parameters, integrating it with smart technologies or advanced control strategies, enhancing its effectiveness in navigating constrained solution spaces. By optimizing energy consumption, CuSA contributes significantly to the long term sustainability of building operations, aligning with green building principles and promoting energy savings with reduced environmental impact [89,90]. CuSA's unique concepts, such as brood parasitism, global exploration, adaptability to dynamic conditions, and avoidance of local optima, collectively position it

as an innovative and holistic tool for building energy conservation, reflecting a fusion of inventive strategies for sustainable and efficient building practices [91]. CuSA maintains a balance between global exploration and local exploitation.

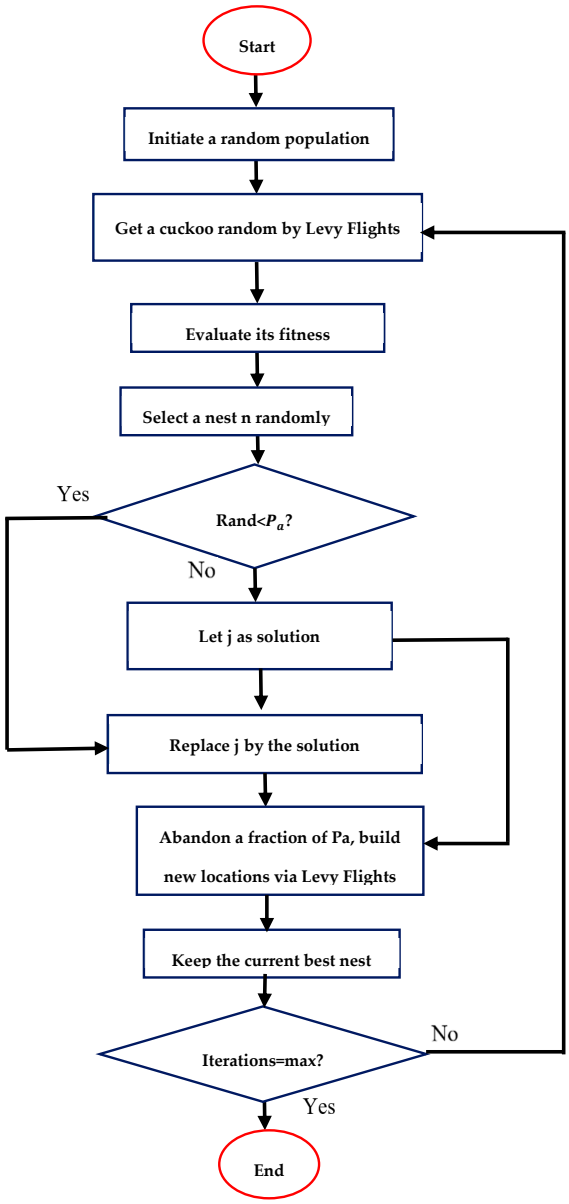


Figure 7. Cuckoo search algorithm (CuSA) flowchart [83].

4.4. Bat Algorithm

The bat algorithm (BA), developed by Xin-She Yang, draws inspiration from the echolocation behavior of microbats [92]. It assumes that bats use echolocation to determine distance, differentiate between prey and objects, and exhibit random flight patterns with variable velocity, wavelength, and pulse rate [93]. Additionally, the algorithm assumes that the loudness of bats' echolocation calls changes within a specified range. The position of each bat is updated based on these assumptions. The algorithm starts by initializing a population of bats with random positions [94]. Each bat uses echolocation to assess the distance to potential prey or obstacles and adjusts its flight velocity accordingly. By varying the wavelength and pulse rate of their echolocation pulses, bats adapt their search behavior. The loudness parameter controls the exploration–exploitation balance, and the bats' positions are updated by adding their current position and the velocity vector. If a bat discovers a better position, the best solution encountered so far is updated. These steps are

repeated for a specified number of iterations or until a termination criterion is met [92,94], allowing the bat algorithm to explore and optimize complex, multimodal search spaces.

$$v_i(t+1) = v_i(t) + f_i\left(x_i(t) - x_g\right) \tag{7}$$

$$x_i(t+1) = x_i(t) + v_i(t+1) \tag{8}$$

where $v_i(t)$ is the current velocity of the ith bat, $v_i(t+1)$ is the updated velocity of the ith bat, $x_i(t)$ is the current position of the ith bat, $x_i(t+1)$ is the updated position of the ith bat, x_g is the global best position, and f_i is the frequency of the ith bat.

A visual representation of the steps involved in executing the BA can be found in Figure 8 [40]. When applied to building energy conservation, BA can help find energy efficient configurations and strategies. BA is used in this context, as follows [95,96]:

1. Define an objective function that represents the energy consumption of the building. This function considers various factors, including heating, cooling, lighting, and equipment energy use.
2. Identify the parameters that can be adjusted to optimize building energy conservation. These parameters include thermostat settings, HVAC system operation schedules, insulation levels, and the use of energy efficient appliances and lighting.
3. Define constraints, such as comfort limits for indoor temperature, humidity, and lighting levels. These constraints ensure that any optimization achieved by the bat algorithm maintains occupant comfort.
4. Develop a building energy simulation model that predicts how changes in the parameters affect energy consumption. This model serves as the basis for evaluating solutions generated by the bat algorithm.
5. Initialize a population of "bat" agents with potential solutions. These agents represent different combinations of parameter values.
6. Evaluate the fitness of each bat agent using the objective function and the building energy model. The fitness function should reflect the energy consumption reduction goal.
7. Apply the bat algorithm rules to update the positions of the bat agents. This involves exploring the solution space and adjusting parameters to minimize energy consumption while maintaining comfort.
8. Determine the convergence criteria, such as a maximum number of iterations or a minimum improvement threshold, to stop the optimization process.
9. Apply the best solution found by the bat algorithm to the real building system. This could involve adjusting building parameters, scheduling energy saving measures, or implementing energy efficient technologies.
10. Continuously monitor building energy consumption to ensure that the optimized parameters and strategies are effective. Periodic maintenance and re-optimization may be necessary to adapt to changing conditions and occupant behavior.

BA's exploration mechanism, inspired by the echolocation behavior of bats, stands as an innovative and thoughtfully designed approach that brings significant value to the dynamic field of building energy conservation [97]. The adaptation of BA's frequency and loudness during the optimization process showcases deep thinking, allowing the algorithm to respond adeptly to environmental changes, including shifts in occupancy patterns, weather conditions, or equipment efficiency [98]. BA's ability to strike a delicate balance between global exploration and local exploitation reflects an innovative strategy essential for efficiently converging to optimal or near optimal solutions while avoiding premature convergence to suboptimal solutions. The real-time adaptability embedded in BA proves advantageous for building energy conservation, where operational conditions undergo dynamic changes [99]. This adaptability enables the algorithm to respond promptly to fluctuations in energy demand, occupancy, or environmental conditions, showcasing a forward thinking approach to addressing the challenges posed by building environments. By optimizing energy consumption, BA contributes substantially to the long term sustain-

ability of building operations [100]. It not only aids in achieving energy savings but also actively participates in reducing environmental impact and aligning with green building principles. BA's exploration strategy, inspired by echolocation, combined with adaptive frequency adjustments and real-time adaptability, positions it as a promising and holistic tool for building energy conservation. This fusion of innovative features aligns seamlessly with the dynamic nature of building environments, actively supporting sustainability and operational efficiency goals [101].

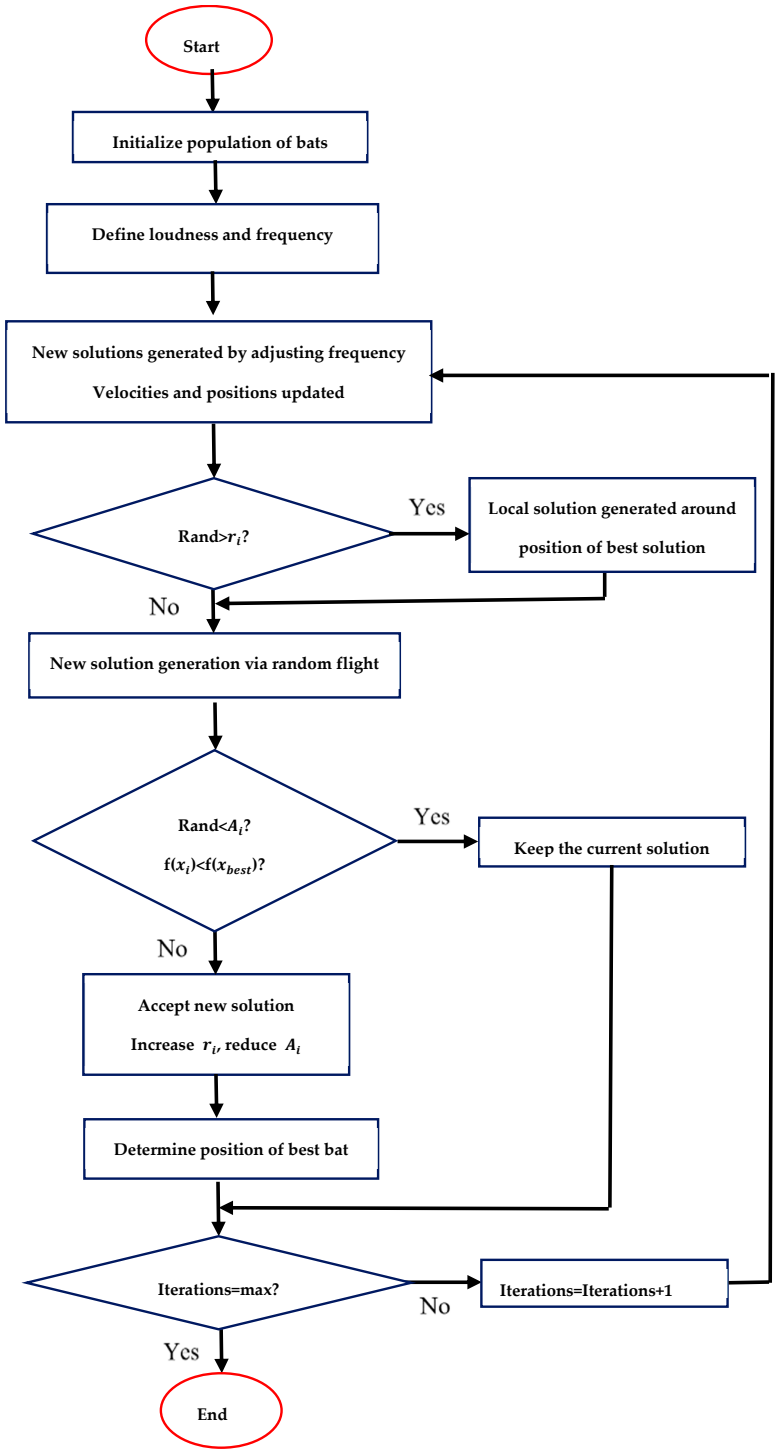


Figure 8. Bat algorithm (BA) flowchart [40].

4.5. Firefly Algorithm

The firefly algorithm (FA), developed in 2007 by Yang, is inspired by the behavior of fireflies and their flashing patterns [102]. This optimization algorithm adheres to four fundamental rules as outlined in references [103,104]. The initial rule specifies that fireflies with lower brightness are drawn toward fireflies that are brighter, without considering gender. The second rule emphasizes that the brightness of a firefly correlates with its attractiveness. Consequently, brighter fireflies are deemed more appealing. The third rule indicates that the attractiveness diminishes as the distance between firefly A and firefly B increases. Finally, the fourth rule states that the brightest firefly moves randomly. The light intensity of a firefly in relation to another firefly is influenced by the distance between them, and this relationship can be expressed as [103–105]:

$$L = L_0 e^{-\delta y^2} \tag{9}$$

where L_0 is the maximum light intensity, L signifies the light intensity perceived by firefly A from firefly B, y is the distance between the two fireflies, and δ is the light absorption, which varies according to the medium in which the firefly exists and typically falls within the range of 0.1 to 10. The attractiveness of firefly B to firefly A is determined based on the light intensity observed, and this is calculated in a similar fashion as the light intensity itself [103,105]. The movement of firefly A towards firefly B can be expressed as follows [104–106]:

$$x_a(t+1) = x_{a,k} + B_0 e^{-\delta {y_{a,b}}^2}(x_{b,k} - x_{a,k}) \; + \; \alpha(rand \; - \; 0.5) \tag{10}$$

where *rand* and α are randomized numbers in the range [0, 1], B_0 is the maximum attractiveness, $x_a(t+1)$ is the updated position of firefly a, $x_{a,k}$ and $x_{b,k}$ are the current positions of fireflies a and b respectively in dimension k, and $y_{a,b}$ is the distance between fireflies a and b.

To execute the FA, the initial step entails defining the necessary parameters. Following this, each firefly is assigned a random position within the search space. Figure 9 [107] offers a visual depiction of the steps involved in executing the FA [108,109]:

1. Define an objective function that represents the energy consumption of the building. This function considers various factors, including heating, cooling, lighting, and equipment energy use.
2. Identify the parameters that can be adjusted to optimize building energy conservation. These parameters include thermostat settings, HVAC system operation schedules, insulation levels, and the use of energy efficient appliances and lighting.
3. Define constraints, such as comfort limits for indoor temperature, humidity, and lighting levels. These constraints ensure that any optimization achieved by the firefly algorithm maintains occupant comfort.
4. Develop a building energy simulation model that predicts how changes in the parameters affect energy consumption. This model serves as the basis for evaluating solutions generated by the firefly algorithm.
5. Initialize a population of "firefly" agents with potential solutions. These agents represent different combinations of parameter values.
6. Evaluate the fitness of each firefly agent using the objective function and the building energy model. The fitness function should reflect the energy consumption reduction goal.
7. Apply the firefly algorithm rules to update the positions of the firefly agents. This involves moving fireflies toward better solutions while maintaining exploration of the solution space.
8. Determine the convergence criteria, such as a maximum number of iterations or a minimum improvement threshold, to stop the optimization process.

9. Apply the best solution found by the firefly algorithm to the real building system. This could involve adjusting building parameters, scheduling energy saving measures, or implementing energy efficient technologies.
10. Continuously monitor building energy consumption to ensure that the optimized parameters and strategies are effective. Periodic maintenance and re-optimization may be necessary to adapt to changing conditions and occupant behavior.

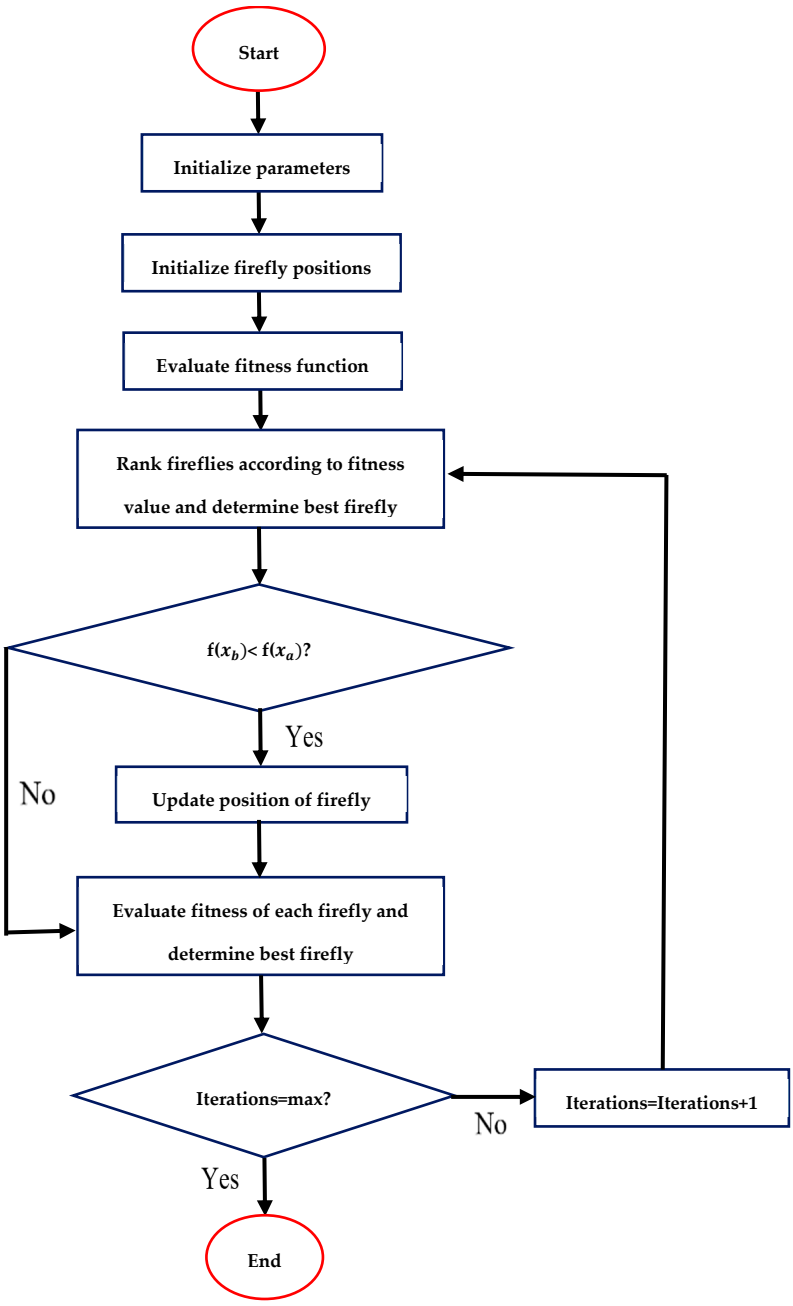


Figure 9. Firefly algorithm (FA) flowchart [107].

The FA's adaptability to dynamic conditions is crucial for building energy conservation. It enables the algorithm to respond to changes in environmental conditions, occupancy patterns, or energy demand, ensuring ongoing optimization [110]. The FA can be adapted to handle constraints effectively. In the context of building energy conservation, where there are often constraints related to comfort levels, indoor air quality, and energy regulations, the algorithm's constraint handling capability is valuable [111,112]. The FA is scalable, making it applicable to various scales of building energy conservation tasks.

Whether optimizing the energy consumption of individual components or entire buildings, the algorithm can adapt to different levels of granularity [113]. By optimizing energy consumption, the FA contributes to the long term sustainability of building operations. It aids in achieving energy savings, reducing environmental impact, and aligning with green building principles. The FA's biological inspiration, attractive–repulsive mechanism, adaptability, global search capability, and scalability make it a promising tool for building energy conservation [114,115]. Its features align with the dynamic nature of building environments, supporting sustainability and operational efficiency goals.

4.6. Strategies Implemented for Energy Conservation in Buildings

The goal of this study was to assess the application of these techniques in the context of energy conservation within a building. Energy conservation in the context of green building optimization is the fundamental goal for sustainable and environmentally friendly construction and operation [116,117]. The work critically assesses and analyses both the advancements in conventional algorithms and their practical application in the context of energy conservation within buildings, filling a gap in the current body of research. Green building optimization, hence, seeks to reduce the environmental impact of buildings while improving energy efficiency. The key strategies implemented for energy conservation in green building optimization are [118–120]:

1. Implementing passive design strategies to optimize natural heating, cooling, and lighting. This includes proper building orientation, shading, natural ventilation, and thermal mass to reduce the need for mechanical heating and cooling.
2. Use of energy efficient insulation materials and designs for walls, roofs, and windows to minimize heat transfer and maintain comfortable indoor temperatures. A well insulated envelope reduces the load on heating and cooling systems.
3. Installing energy efficient heating, ventilation, and air conditioning (HVAC) systems that use advanced technologies such as heat pumps, variable refrigerant flow (VRF) systems, and energy recovery ventilation. These systems reduce energy consumption while maintaining indoor comfort.
4. Incorporating renewable energy sources, such as solar panels, wind turbines, and geothermal systems, to generate clean energy on site. This helps offset energy consumption and reduce reliance on fossil fuels.
5. Implementing smart energy management systems that control and optimize various building systems, including lighting, HVAC, and appliances, to minimize energy usage. These systems can be programmed to adapt to occupancy patterns and changing weather conditions.
6. Replacing traditional lighting with energy efficient LED fixtures and incorporate daylight harvesting systems. These systems adjust artificial lighting based on natural light availability, reducing energy consumption.
7. Installing energy efficient appliances, equipment, and fixtures throughout the building. This includes Energy Star rated appliances, water saving fixtures, and efficient office equipment.
8. Using occupancy sensors and smart building controls to adjust lighting, HVAC, and ventilation based on real-time occupancy data. Unoccupied areas can be set to energy saving modes.
9. Implementing BAS to monitor and control various building systems for optimal performance and energy conservation. BAS can coordinate HVAC, lighting, security, and other systems to maximize energy efficiency.
10. Participate in demand response programs offered by utilities to reduce energy consumption during peak periods. These programs can provide financial incentives for energy conservation.
11. Seek green building certifications, such as LEED (Leadership in Energy and Environmental Design), to ensure that the building design and operation meet rigorous sustainability and energy efficiency standards.

12. Continuously monitor and analyse energy consumption data to identify areas for improvement. Regularly optimize building systems and operations to maintain energy efficiency over time.

Energy conservation in green building optimization is essential for reducing energy costs, minimizing greenhouse gas emissions, and creating healthier, more sustainable environments for occupants. It combines passive design strategies, efficient building systems, renewable energy integration, and smart technologies to achieve these goals. A comparative analysis of green building optimization involves assessing and contrasting various approaches, strategies, and techniques used to improve the sustainability and energy efficiency of buildings. A comparative analysis of some methods employed in green building optimization are as follows:

4.6.1. Passive Design vs. Active Systems

- Passive design focuses on architectural features and building orientation to harness natural resources such as sunlight, airflow, and thermal mass for heating, cooling, and lighting. It relies on the building's inherent characteristics [121].
- Active systems involve the use of mechanical and electrical technologies, such as HVAC systems, LED lighting, and energy management systems, to enhance energy efficiency. These systems require energy to operate [121].

Passive design is cost effective and environmentally friendly but has limitations in extreme climates. Active systems provide precise control but consume more energy and have higher installation costs.

4.6.2. Renewable Energy Integration

- Solar panels capture sunlight and convert it into electricity or heat for building use [122].
- Wind turbines generate electricity from wind energy, which can be used to power buildings.
- Geothermal heat pumps use the Earth's temperature to heat and cool buildings efficiently [122].

The choice of renewable energy source depends on location, available resources, and cost effectiveness. Solar panels are widely used and cost effective. Wind turbines are suitable in areas with consistent wind. Geothermal systems are efficient but may require specific geological conditions.

4.6.3. Energy Management Systems (EMS)

- BAS integrates and controls various building systems, including HVAC, lighting, and security, to optimize energy use [123].
- Occupancy sensors detect movement and adjust lighting and HVAC settings in response to occupancy patterns [123].

BAS offers comprehensive control and can be expensive to implement. Occupancy sensors are cost effective and suitable for smaller buildings.

4.6.4. Green Building Certifications

- LEED is a widely recognized certification system that promotes green building practices. It assesses a building's sustainability in various categories, including energy efficiency [124].
- BREEAM is another certification system that evaluates the sustainability and environmental performance of buildings [125].

LEED and BREEAM have similar goals but may use different assessment criteria and methodologies. The choice depends on regional preferences and project-specific goals.

4.6.5. Smart Grid Integration

- Buildings can interact with smart grids to optimize energy consumption based on real-time grid conditions and pricing signals [126].
- Demand response programs allow buildings to reduce energy use during peak demand periods to support grid stability [126].

Smart grid integration and demand response are crucial for load balancing and cost reduction. However, participation and effectiveness may vary depending on location and utility programs.

4.6.6. Continuous Monitoring and Optimization

- Continuous monitoring of building systems and energy consumption data allows for ongoing optimization [127].
- Periodic assessments and retro-commissioning activities help identify opportunities for improvement [127].

Continuous monitoring is essential for real-time adjustments but may require advanced technology and expertise. Periodic assessments are valuable for long term optimization.

4.7. Comparative Evaluation of MOTs Researched

Table 5 indicates the applications of each of the metaheuristic model's superiority in the green building environment for achieving energy conservation and its year of most recent research. The timing of developments shown in Table 5 indicates the applications after the initial period of suggestion. A summary is provided of the discussed swarm-based MOTs and their application to achieving energy conservation in buildings. The table includes information about the advantages, disadvantages, and applications of each technique. The development of PSO has been a significant advancement in the field of optimization. It has been widely utilized to solve various optimization problems. PSO has also served as the foundation for the emergence of other swarm-based MOTs. However, the theoretical basis of PSO is relatively basic compared to the complex and intelligent behavior exhibited by flocks of birds and schools of fish in practice. Incorporating more advanced intelligent behavior of birds and fish into the PSO algorithm, it has the potential to further improve its performance and make it a superior optimization technique once again. The concepts underlying the CuSA are interesting. However, the equations employed in these algorithms may not be complex enough to fully simulate the relative behavior observed in nature. Overall, while these swarm-based MOTs have shown promise, further research and the exploration of more sophisticated behavior and equations inspired by the natural systems they aim to simulate could potentially enhance their performance and address their limitations.

Table 5. Summary applications of MOTs researched.

Swarm Intelligence Technique	Advantages	Disadvantages	Exploration vs. Exploitation	Parameter Sensitivity	Significant findings to Green Building Application	Year of Recent Development
Particle Swarm Optimization [57–64]	• Simplicity and ease of implementation. • Quickly converge to optimal solutions, making it suitable for many optimization problems. • Effective in finding near-optimal solutions in multidimensional search spaces.	• Limitations in handling discrete optimization problems common in building design. • Sensitive to the choice of parameters such as inertia weight and learning factors. • Require fine tuning for optimal performance in specific applications.	Balanced	Moderate	• Energy efficiency optimization • Renewable energy integration • Optimal building design • Smart building controls • Indoor comfort optimization *Ease of implementation—Better*	2020
Artificial Bee Colony [71–79]	• Inspired by the foraging behavior of honeybees and is effective in handling discrete optimization problems. • It can be particularly useful in combinatorial optimization, which is common in building design.	• Require more iterations to converge, making it computationally expensive in some cases. • The algorithm's performance can be sensitive to the number of scout bees and employed bees.	Balanced	Sensitive	• Building system optimization • Building design optimization • Smart building controls • Cost effective solutions • Indoor environment quality optimization *Ease of implementation—Good*	2019
Cuckoo Search Optimization [84–91]	• Inspired by the brood parasitism behavior of cuckoos, making it suitable for optimization problems with a global search space. • Robust and can effectively handle nonlinear, multimodal optimization problems.	• Computationally expensive and requires many iterations to converge to optimal solutions. • Fine tuning parameters can be challenging, and it may not always outperform other algorithms.	Exploration—Focused	Moderate	• HVAC system optimization • Optimal building envelope design • Energy efficient lighting systems • Indoor environment quality enhancement • Smart building design *Ease of implementation—Good*	2023

Table 5. *Cont.*

Swarm Intelligence Technique	Advantages	Disadvantages	Exploration vs. Exploitation	Parameter Sensitivity	Significant findings to Green Building Application	Year of Recent Development
Bat Algorithm [95–101]	• Inspired by the echolocation behavior of bats and is effective in continuous optimization problems. • Adapt to dynamic environments and is suitable for real-time optimization.	• Does not perform as well in discrete optimization problems and can be sensitive to parameter settings. • Require additional techniques to address premature convergence issues.	Balanced	Sensitive	• Smart building design • Optimization of building energy systems • Adaptability to complex systems • HVAC system optimization • Cost effective solutions *Ease of implementation—Good*	2023
Firefly Algorithm [108–117]	• Inspired by the flashing behavior of fireflies and can effectively address optimization problems with global search spaces. • Used successfully in a wide range of applications and can provide good results in multimodal optimization.	• Limitations in handling discrete optimization problems, similar to PSO. • The choice of parameters in FA can impact its performance.	Exploration—Focused	Moderate	• Natural lighting optimization • Thermal comfort in HVAC systems • Building envelope design • Integration of smart building technologies • Life cycle assessments *Ease of implementation—Good*	2021

ABC, FA, and BA are considered complex in their structure and attempt to capture various features of their corresponding swarms. However, there are certain characteristics missing in these algorithms that could be explored for further enhancement. For instance, in a bee colony, the queen bee plays a crucial role. Investigating the incorporation of the queen bee's behavior could potentially improve the performance of ABC. The same suggestion applies to BA, which is inspired by the behavior of microbats. While BAs have shown promise, further rigorous testing and application are necessary to validate their capabilities. This also applies to other techniques, such as FA.

The literature provides several comparisons between conventional optimization techniques. In one comparison between ABC and PSO [115], both algorithms exhibit similar characteristics for unimodal functions, but ABC outperforms PSO for multimodal functions. The sensitivity of ABC to population and dimension sizes highlights a research area that requires further investigation. Another comparison [116] involves PSO, FA, ABC, CSA, and GWO. GWO performs well in unimodal functions, outperforming other techniques in six out of seven cases. However, it struggles with standard multimodal functions. CSA, on the other hand, produces the lowest average results, indicating the need for improvements in this technique. Another comparison [117] involves BA and BFO applied to various benchmark functions. BFO demonstrates superior accuracy, while BA exhibits a faster convergence rate. These comparative studies provide valuable insights into the performance and characteristics of different optimization techniques, highlighting their strengths, weaknesses, and areas for further improvement.

5. Results and Discussion of Techniques Reviewed

The optimization techniques undergo a thorough examination, encompassing their inception, mathematical modelling, application process, advantages, disadvantages, and advancements. The goal was to assess the application of these techniques in the context of energy conservation within buildings. In this study, a comparative analysis of three optimization techniques—PSO, ABC, and FA—was carried out. These techniques were applied to three benchmark functions as in Table 6, each assessed at three different dimensions (5, 50, and 100). To ensure a fair comparison, the number of search agents and particles remained consistent across all three algorithms. This approach allowed for the evaluation and comparison of the performance of these optimization algorithms across various problem types and dimensions, providing insights into their convergence and solution quality under different conditions.

Table 6. Benchmark functions details.

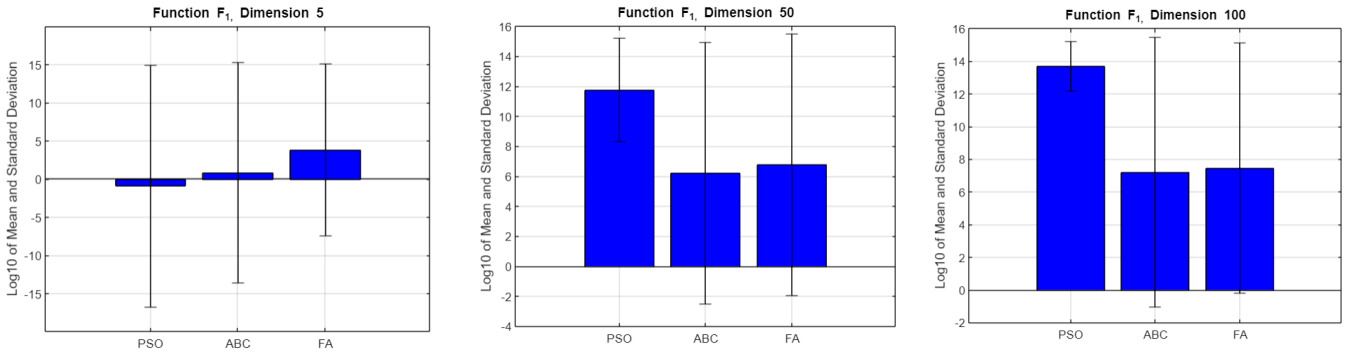
Function	Description	Range	f_{min}
F_1	$\sum_{i=2}^{d} i\left(2x_i^2 - x_{i-1}\right)^2 + (x_1 - 1)^2$	$[-10, 10]$	0
F_2	$\frac{1}{4000}\sum_{i=1}^{d} x_i^2 - \prod_{i=1}^{d} \cos\left(\frac{x_i}{\sqrt{i}}\right) + 1$	$[-600, 600]$	0
F_3	$\sum_{i=1}^{d}\left[x_i^2 - 10\cos(2\pi x_i)\right] + 10d$	$[-5.12, 5.12]$	0

The experimental setup involved conducting 20 independent runs for each MOT due to the stochastic nature of these algorithms. Table 7 summarizes the outcomes, presenting both average values and standard deviations obtained from these multiple runs. Additionally, a bar plot is provided to visually compare the mean values, and error bars are incorporated to illustrate the spread of the data, offering insights into the convergence patterns. This comprehensive approach accounts for variability in algorithm performance and provides a robust assessment of their effectiveness across multiple iterations.

Table 7. Comparison of three benchmark functions.

Dimension	Function		PSO	ABC	FA
5	F_1	Mean	0.13	6.89	6959
		Std.	1.39×10^{-16}	3.56×10^{-15}	5.47×10^{-12}
	F_2	Mean	7.06×10^{11}	1.6×10^{6}	6.19×10^{6}
		Std.	1.39×10^{-16}	9.34×10^{-10}	6.54×10^{-9}
	F_3	Mean	5.26×10^{11}	1.61×10^{7}	2.71×10^{7}
		Std.	0.02	3.74×10^{-9}	7.45×10^{-9}
50	F_1	Mean	5.8×10^{11}	1.6×10^{6}	6.2×10^{6}
		Std.	3.7×10^{-4}	1.9×10^{-9}	1.9×10^{-9}
	F_2	Mean	28.94	342.7	1098
		Std.	2.14×10^{-14}	1.14×10^{-13}	6.84×10^{-14}
	F_3	Mean	1.29×10^{5}	724.9	709.5
		Std.	1.17×10^{-10}	3.42×10^{-13}	1.14×10^{-13}
100	F_1	Mean	4.8×10^{13}	1.6×10^{7}	2.9×10^{7}
		Std.	0.03	5.6×10^{-9}	2.2×10^{-8}
	F_2	Mean	494.7	1211	2488
		Std.	3.42×10^{-13}	9.12×10^{-13}	2.74×10^{-12}
	F_3	Mean	2.08×10^{6}	1612	1538
		Std.	1.4×10^{-9}	1.14×10^{-12}	2.28×10^{-13}

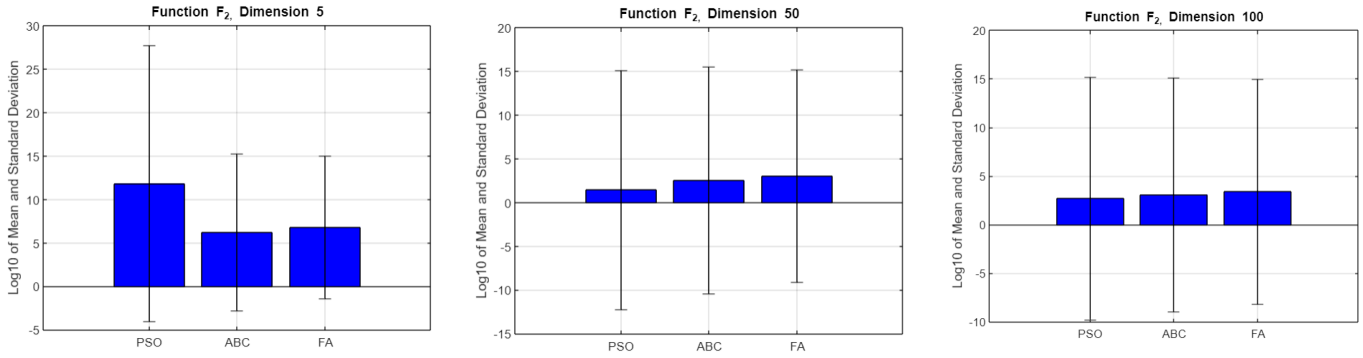
In Figure 10a, the results indicate that at 5D, PSO achieves the lowest mean value (0.13) with an almost negligible standard deviation, showcasing precise and consistent convergence to the optimal solution. ABC performs well with a slightly higher mean (6.89) and a very small standard deviation, indicating good convergence, but potentially to a different region. On the other hand, FA exhibits a significantly higher mean value (6959) with a small standard deviation, suggesting convergence to a distinct region, possibly a local minimum. In Figure 10b, at 50D, PSO demonstrates convergence to a specific region with a large objective function value (5.8×10^{11}) and a relatively small standard deviation. ABC achieves a much lower mean value (1.6×10^{6}) with a small standard deviation, pointing to convergence in a different region with a lower objective function value. FA shows a mean value (6.2×10^{6}) with a standard deviation similar to ABC, indicating convergence to another region, possibly with a higher objective function value. In Figure 10c, at 100D, PSO exhibits very high mean value convergence (4.8×10^{13}) with a small standard deviation, indicating convergence to a specific region with an extremely large objective function value. ABC, with a much lower mean value (1.6×10^{7}) and a small standard deviation, converges to a different region with a lower objective function value. FA, with a mean value (2.9×10^{7}) and a standard deviation similar to ABC, suggests convergence to another region, possibly with a higher objective function value.



(**a**) (**b**) (**c**)

Figure 10. F1 mean values and error bars towards convergence at (**a**) 5D, (**b**) 50D, and (**c**) 100D.

In Figure 11a, the results reveal that at 5D, PSO achieves a very high mean value (7.06×10^{11}) with an extremely small standard deviation, signifying convergence to a specific region with an exceptionally large objective function value. ABC, with a much lower mean value (1.6×10^{6}) and a small standard deviation, converges to a different region with a lower objective function value. FA exhibits a mean value (6.19×10^{6}) with a slightly larger standard deviation compared to ABC, suggesting convergence to another region, possibly with a higher objective function value. In Figure 11b, at 50D, PSO achieves a mean value (28.94) with a relatively small standard deviation, indicating convergence to a specific region with a moderate objective function value. ABC, with a much lower mean value (342.7) and a small standard deviation, converges to a different region with a lower objective function value. FA shows a mean value (1098) with a larger standard deviation compared to ABC, hinting at convergence to a different region, possibly with a higher objective function value. In Figure 11c, at 100D, PSO achieves a mean value (494.7) with a very small standard deviation, signifying convergence to a specific region with a moderate objective function value. ABC, with a mean value (1211) and a small standard deviation, converges to a different region with a lower objective function value. FA exhibits a mean value (2488) with a larger standard deviation compared to PSO and ABC, suggesting convergence to a different region, possibly with a higher objective function value.



(**a**) (**b**) (**c**)

Figure 11. F2 mean values and error bars towards convergence at (**a**) 5D, (**b**) 50D, and (**c**) 100D.

In Figure 12a, at 5D, PSO achieves a mean value (5.26×10^{11}) with a small standard deviation, indicating convergence to a specific region with a large objective function value. ABC, with a mean value (1.61×10^{7}) and a small standard deviation, converges to a different region with a lower objective function value. FA exhibits a mean value (2.71×10^{7}) with a slightly larger standard deviation compared to ABC, suggesting convergence to another region, possibly with a higher objective function value. In Figure 12b, at 50D, PSO achieves a mean value (1.29×10^{5}) with a very small standard deviation, indicating convergence to a specific region with a moderate objective function value. ABC, with a mean value (724.9) and a small standard deviation, converges to a different region with a lower objective function value. FA shows a mean value (709.5) with an extremely small standard deviation, suggesting convergence to a different region, possibly with a higher objective function value. In Figure 12c, at 100D, PSO achieves a mean value (2.08×10^{6}) with a small standard deviation, indicating convergence to a specific region with a moderate objective function value. ABC, with a mean value (1612) and a very small standard deviation, converges to a different region with a lower objective function value. FA exhibits a mean value (1538) with an extremely small standard deviation, suggesting convergence to a different region, possibly with a higher objective function value. At 5D, in Figure 12a, PSO achieves a mean value (5.26×10^{11}) with a small standard deviation. This indicates convergence to a specific region with a large objective function value. ABC has a mean value (1.61×10^{7}) with a small standard deviation. This indicates convergence to a different region with a lower objective function value. FA shows a mean value (2.71×10^{7}) with a slightly larger standard

deviation compared to ABC. This suggests convergence to a different region, possibly with a higher objective function value.

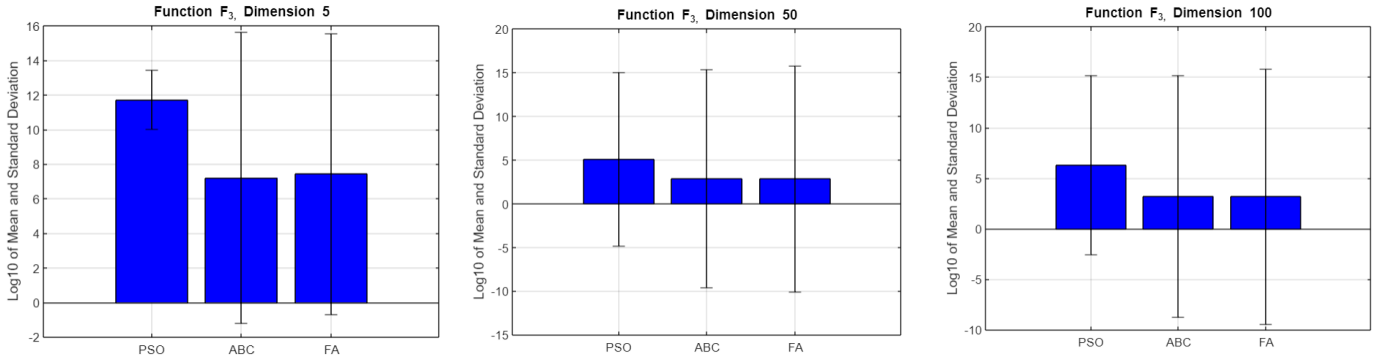


Figure 12. F3 mean values and error bars towards convergence at (**a**) 5D, (**b**) 50D, and (**c**) 100D.

6. Conclusions

This paper presents a review of swarm-based MOTs, focusing on their algorithm structure, advantages, disadvantages, and applications in achieving energy conservation in buildings. Although numerous swarm-based MOTs exist, this paper covers five specific techniques. The featured swarm-based techniques are PSO, ABC optimization, CuSA, BA, and FA. The paper provides insights into the underlying theories and mathematical models of these algorithms. It is notable that these algorithms, despite their variations in structure and optimization methods, share a commonality in their stochastic nature. When exploring the applications of swarm-based MOTs in engineering, various examples can be found. While these techniques generally exhibit strong performance, many conventional algorithms suffer from drawbacks, such as poor convergence rates and susceptibility to being trapped in local minima. Considering the application of swarm-based MOTs to energy conservation in buildings, it is observed that only PSO has been thoroughly researched and applied. Other algorithms, such as ABC optimization, CuSA, BA, and FA, have been applied only once or twice as part of this paper. Although swarm-based metaheuristic optimization techniques have demonstrated promising outcomes when utilized in building applications, it is essential to acknowledge the limited number of applications and rigorous testing of these methods. Hence, comprehensive testing is imperative to confirm their effectiveness. There is a need for further research and the application of these algorithms, especially those that have not been thoroughly explored in the context of energy conservation in buildings. The proposed future scope of work includes:

- Utilizing the improved swarm-based MOTs, as deliberated in the paper, for the purpose of achieving energy conservation in buildings.
- Exploring various swarm-based MOTs, encompassing an examination of their structure, mathematical models, limitations, advancements, and their relevance when applied to the domain of energy conservation within building environments.
- The combination of multiple MOTs to create hybrid algorithms that can be applied to green buildings.

By addressing these areas of research, a more comprehensive understanding of swarm-based MOTs and their application to energy conservation in buildings can be achieved, ultimately leading to potentially improved optimization strategies.

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Abbreviations

ABC	Ant Bee Colony
ACO	Ant Colony Optimization
AFSA	Artificial Fish Swam Optimization
ALO	Ant Lion Optimization
ATES	Aquifer Thermal Energy Storage
BA	Bat Algorithm
BACS	Building Automation and Control Systems
BBCB	Big Bang–Big Crunch Optimization
BCO	Border Collide Optimization
BEPM	Building Energy Performance Monitoring
BES	Bald Eagle Search
BFGS	Broyden–Fletcher–Goldfarb–Shanno
BFO	Bacteria Foraging Optimization
BOA	Butterfly inspired Algorithm
BPSO	Binary Particle Swarm Optimization
BSO	Brain Storm Optimization
CuSA	Cukoo Search
CSA	Crow Search Algorithm
CSO	Chicken Swarm Optimization
DA	Dragonfly Algorithm
DE	Differential Evolution
DMFC	Direct Methanol Fuel Cells
DS	Differential Search
EEMD	Ensemble Empirical Mode Decomposition
EO	Equilibrium Optimizer
EP	Evolutionary Programming
ERV	Energy Recovery Ventilation
ES	Evolution Strategy
FA	Firefly Algorithm
FANET	Flying Ad-Hoc Networks
FSS	Frequency Selective Surface
GA	Genetic Algorithm
GOA	Grasshopper Optimization Algorithm
GSA	Gravitational Search Algorithm
GSK	Gaining Sharing Knowledge
GWO	Grey Wolf Optimization
HGSO	Henry Gas Solubility Optimization
HHO	Harris Hawk Optimization
HIA	Human inspired Algorithm
HVAC	Heating, Ventilation and Air Conditioning
HS	Harmony Search
IEA	International Energy Agency
IoT	Internet of Things

KH	Krill Herd Algorithm
LSA	Lightning Search Algorithm
MBA	Mine Blast Algorithm
MOT	Metaheuristic Optimization Techniques
MVO	Multiverse Optimize
MWOA	Modified Whale Optimization Algorithm
PCM	Physarum-inspired Computational Model
PFGM	Potential Field Guidance Mechanism
PSO	Particle Swarm Optimization
RFD	River Formation Dynamics
RO	Ray Optimization
SA	Simulated Annealing
SCA	Since Cosine Algorithm
SCE	Simultaneous Contrast Enhancement
SEOA	Social Emotional Optimization
SFO	Synergistic Fibroblast Optimization
SMA	Slime Mould Algorithm
SSA	Salp Swarm Optimization
TEO	Thermal Exchange Optimization
TGWO	Tracking Grey Wolf Optimization
TLBO	Teaching–learning Base Optimization
TS	Tabu Search
TS-GWO	Tracking–Seeking Grey Wolf Optimization
UAV	Unmanned Aerial Vehicles
VRF	Variable Refrigerant Flow
VPL	Volleyball Premier League Algorithm
WOA	Whale Optimization Algorithm

References

1. Khan, A.Z. Electrical energy conservation and its application to a sheet glass industry. *IEEE Trans. Energy Conserv.* **1996**, *11*, 666–671. [CrossRef]
2. Nouiri, M.; Trentesaux, D.; Bekrar, A. Towards Energy Efficient Scheduling of Manufacturing Systems through Collaboration between Cyber Physical Production and Energy Systems. *Energies* **2019**, *12*, 4448. [CrossRef]
3. Wong, J.K.; Li, H. Application of the analytic hierarchy process (AHP) in multi-criteria analysis of the selection of intelligent building systems. *Build. Environ.* **2008**, *43*, 108–125. [CrossRef]
4. Chen, S.; Zhang, G.; Xia, X.; Setunge, S.; Shi, L. A review of internal and external influencing factors on energy efficiency design of buildings. *Energy Build.* **2020**, *216*, 109944. [CrossRef]
5. Gholamzadehmir, M.; Del Pero, C.; Buffa, S.; Fedrizzi, R.; Aste, N. Adaptive-predictive control strategy for HVAC systems in smart buildings—A review. *Sustain. Cities Soc.* **2020**, *63*, 102480. [CrossRef]
6. MDPI. Open Access Journals A–Z. Available online: https://www.mdpi.com/about/journals (accessed on 19 September 2022).
7. Elsevier. ScienceDirect. Available online: https://www.sciencedirect.com/ (accessed on 10 June 2022).
8. van Eck, N.J.; Waltman, L. VOSviwer. In *Centre for Science and Technology Studies*; Leiden University: Leiden, The Nethelands, 2020. Available online: https://www.vosviewer.com/ (accessed on 14 August 2021).
9. Alam, M.R.; Reaz, M.B.I.; Ali, M.A.M. A Review of Smart Homes—Past, Present, and Future. *IEEE Trans. Syst. Man Cybern. Part C Appl. Rev.* **2012**, *42*, 1190–1203. [CrossRef]
10. Lutolf, R. Smart Home Concept and the Integration of Energy Meters into a Home Based System. In Proceedings of the Seventh International Conference on Metering Apparatus and Tariffs for Electricity Supply, Glasgow, UK, 17–19 November 1992; IET: London, UK, 1992; pp. 277–278.
11. Tien, P.W.; Wei, S.; Darkwa, J.; Wood, C.; Calautit, J.K. Machine Learning and Deep Learning Methods for Enhancing Building Energy Efficiency and Indoor Environmental Quality—A Review. *Energy AI* **2022**, *10*, 100198. [CrossRef]
12. GBPN. Buildings for Our Future, The Deep Path for Closing the Emissions Gap in the Building Sector. Green Buildings Performance Network. 2012. Available online: www.gbpn.org/reports (accessed on 23 November 2023).
13. UNEP-SBCI. South African Report on Greenhouse Gas Emission Reduction Potentials from Buildings; A Discussion Document. United Nations Environment Programme, Sustainable Building and Climate Initiative. Undertaken by the CIDB. 2009. Available online: www.unep.org/sbci (accessed on 15 October 2023).
14. Ng, C.H.; Logenthiran, T.; Woo, W.L. Intelligent distributed smart grid network-Reconfiguration. In Proceedings of the 2015 IEEE Innovative Smart Grid Technologies-Asia ISGT ASIA, Bangkok, Thailand, 3–6 November 2015; pp. 1–6.
15. Hussain, I.; Ullah, M.; Ullah, I.; Bibi, A.; Naeem, M.; Singh, M.; Singh, D. Optimizing Energy Consumption in the Home Energy Management System via a Bio-Inspired Dragonfly Algorithm and the Genetic Algorithm. *Electronics* **2020**, *9*, 406. [CrossRef]

16. Wright, C.; Baur, S.; Grantham, K.; Stone, R.B.; Grasman, S.E. Residential energy performance metrics. *Energies* **2010**, *3*, 1194–1211. [CrossRef]
17. Yang, Z.; Wang, Y.; Zhu, L. Building space heating with a solar-assisted heat pump using roof-integrated solar collectors. *Energies* **2011**, *4*, 504–516. [CrossRef]
18. Liao, K.S.; Yambem, S.D.; Haldar, A.; Alley, N.J.; Curran, S.A. Designs and architectures for the next generation of organic solar cells. *Energies* **2010**, *3*, 1212–1250. [CrossRef]
19. Jacob, B. Lamps for improving the energy efficiency of domestic lighting. *Light. Res. Technol.* **2009**, *41*, 219–228. [CrossRef]
20. Sailor, D.J. A green roof model for building energy simulation programs. *Energy Build.* **2008**, *40*, 1466–1478. [CrossRef]
21. International Energy Agency. *2019 Global Status Report for Buildings and Construction*; Tech. Rep.; International Energy Agency: Paris, France, 2019; p. 41.
22. Kim, D.; Yoon, Y.; Lee, J.; Mago, P.J.; Lee, K.; Cho, H. Design and Implementation of Smart Buildings: A Review of Current Research Trend. *Energies* **2022**, *15*, 4278. [CrossRef]
23. Miceli, R. Energy management and smart grids. *Energies* **2013**, *6*, 2262–2290. [CrossRef]
24. DPW; National Treasury; Salga; DFID; DBSA. Guidelines for the Implementation of Labour-Intensive Infrastructure Projects under the Expanded Public Works Programme, 2nd ed.; July 2005. Available online: www.epwp.gov.za (accessed on 5 November 2023).
25. Danish, E.M. *Development of Post-2015 National Energy Efficiency Strategy, Targets, Measures and Implementation Plan*; Department of Energy: Gauteng, South Africa, 2016; pp. 2–3.
26. GBCSA. *Green Building of South Africa Guide*; GBCSA: Cape Town, South Africa, 2015; pp. 12–36.
27. Attia, S.; Hamdy, M.; O'Brien, W.; Carlucci, S. Assessing gaps and needs for integrating building performance optimization tools in net zero energy buildings design. *Energy Build.* **2013**, *60*, 110–124. [CrossRef]
28. Zhao, Z.; Lee, W.C.; Shin, Y.; Song, K.B. An optimal power scheduling method for demand response in home energy management system. *IEEE Trans. Smart Grid* **2013**, *4*, 1391–1400. [CrossRef]
29. Agarwal, R.; Jadhav, S.S.; Zope, S.R.; Sapatnekar, S.S. Energy conservation in buildings using smart technologies: A review. In Proceedings of the 2016 IEEE 1st International Conference on Power Electronics, Intelligent Control and Energy Systems (ICPEICES), Delhi, India, 4–6 July 2016.
30. Maleki, A.; Shayanfar, H.A. Building Energy Management Systems: A Review on Optimization Techniques and Strategies. In Proceedings of the 2019 IEEE International Conference on Energy Internet (ICEI), Nanjing, China, 27–31 May 2019.
31. Kamis, M.S.B.M.; Noor, M.N.M.; Sahibuddin, S.; Noor, M.N.M. Review of energy conservation measures and strategies for sustainable commercial buildings. In Proceedings of the 2019 IEEE 9th Symposium on Computer Applications & Industrial Electronics (ISCAIE), Kota Kinabalu, Malaysia, 27–28 April 2019.
32. Saxena, P.; Rathore, N.S.; Rathore, A.S. Energy conservation in green buildings: A comprehensive review. In Proceedings of the 2018 IEEE International Conference on Energy, Communication, Data Analytics and Soft Computing (ICECDS), Coimbatore, India, 19 June 2018.
33. Sayah, S. Energy management strategies for green buildings: A review. In Proceedings of the 2016 IEEE International Renewable and Sustainable Energy Conference (IRSEC), Piscataway, NJ, USA, 14–17 November 2016.
34. Rahman, S.F.A.; Kadir, M.R.A.; Osman, I. Energy efficiency in green buildings: A review on the use of building automation system. In Proceedings of the 2018 IEEE International Conference on Power and Energy (PECon), Kuala Lumpur, Malaysia, 3–4 December 2018.
35. Zhou, J.; Love, P.E.; Wang, X.; Teo, K.L.; Irani, Z. A review of methods and algorithms for optimising construction scheduling. *J. Oper. Res. Soc.* **2013**, *64*, 1091–1105. [CrossRef]
36. Lashkari, B.; Chen, Y.; Musilek, P. Energy Management for Smart Homes—State of the Art. *Appl. Sci.* **2019**, *9*, 3459. [CrossRef]
37. Weglarz, J. (Ed.) *Project Scheduling: Recent Models, Algorithms and Applications*; Springer Science & Business Media: Berlin/Heidelberg, Germany, 2012; Volume 14.
38. Ibadov, N. Fuzzy estimation of activities duration in construction projects. *Arch. Civ. Eng.* **2015**, *61*, 23–34. [CrossRef]
39. Hussein, A.G.; Amin, M.; Wang, M.; Liang, G.; Alsanad, A.; Gumaei, A. Crow search algorithm: Theory, recent advances, and applications. *IEEE Access* **2020**, *8*, 173548–173565. [CrossRef]
40. Hashim, F.A.; Houssein, E.H.; Mabrouk, M.S.; Al-Atabany, W.; Mirjalili, S. Henry gas solubility optimization: A novel physics based algorithm. *Future Gener. Comput. Syst.* **2019**, *101*, 646667. [CrossRef]
41. Mirjalili, S. Moth-flame optimization algorithm: A novel nature inspired heuristic paradigm. *Knowl.-Based Syst.* **2015**, *89*, 228–249. [CrossRef]
42. Topal, A.O.; Altun, O. A novel meta-heuristic algorithm: Dynamic virtual bats algorithm. *Inf. Sci.* **2016**, *354*, 222–235. [CrossRef]
43. Gao, W.; Hu, Y.; Chau, C.K. A review of building energy regulations and policies in China during the 11th five-year plan. *Energy Policy* **2015**, *86*, 178–189.
44. Ma, Z.; Li, Y.; Wang, Y.; Guo, Y. Optimization model and strategy for the comprehensive energy system in eco-industrial parks. *Appl. Energy* **2017**, *185*, 1670–1680.
45. Jalayer, M.; Fujiwara, O. A review on building energy consumption forecasting. *Renew. Sustain. Energy Rev.* **2018**, *81*, 2441–2460.
46. Asadi, E.; Omer, A.M.; Hossain, M.S. A review on building energy consumption and potential savings through implementation of advanced thermal comfort models. *Renew. Sustain. Energy Rev.* **2019**, *101*, 132–152.

47. Kusiak, A.; Zheng, H.; Song, Z.; Kim, S. Prediction of energy consumption of a building: A neural networks approach. *Energy Build.* **2010**, *42*, 623–630.
48. Yang, X.S. A new metaheuristic bat-inspired algorithm. In *Nature Inspired Cooperative Strategies for Optimization (NICSO 2010)*; Springer: Berlin/Heidelberg, Germany, 2010; pp. 65–74.
49. del Valle, Y.; Venayagamoorthy, G.K.; Mohagheghi, S.; Hernandez, J.; Harley, R.G. Particle swarm optimization: Basic concepts. *IEEE Trans. Evol. Comput.* **2008**, *12*, 171–195. [CrossRef]
50. Boeringer, D.W.; Werner, D.H. Particle swarm optimization versus genetic algorithms for phased array synthesis. *IEEE Trans. Antennas Propag.* **2004**, *52*, 771–779. [CrossRef]
51. Kennedy, J.; Eberhart, R. Particle swarm optimization. In Proceedings of the ICNN'95—International Conference on Neural Networks, Perth, WA, Australia, 27 November–1 December 1995.
52. Kennedy, J.; Eberhart, R. A new optimizer using particle swarm theory. In Proceedings of the Sixth International Symposium on Micro Machine and Human Science, Nagoya, Japan, 4–6 October 1995.
53. Pillay, N. A Particle Swarm Optimization Approach for Tuning of SISO PID Control Loops. 2008. Available online: https://openscholar.dut.ac.za/bitstream/10321/488/3/Pillay_2008.pdf (accessed on 14 November 2023).
54. Tleis, T. Modelling of ac rotating machines. In *Power Systems Modelling and Fault Analysis: Theory and Practice*; Elsevier: Amsterdam, The Netherlands, 2008; pp. 371–468.
55. Soumya, C.; Rao, R. Design of a harmonic filter for a grid connected. *Int. J. Innov. Technol. Explor. Eng.* **2020**, 928–950. [CrossRef]
56. Najjarpour, M.; Jalalifar, H. Optimization of Fairhurst-Cook Model for 2-D Wing Cracks Using Ant Colony Optimization (ACO), Particle Swarm Intelligence (PSO), and Genetic Algorithm (GA). *J. Appl. Math. Phys.* **2018**, *6*, 1581–1595. [CrossRef]
57. Prajapati, A.; Kumar, S. PSO-MoSR: A PSO-based multi-objective software remodularization. *Int. J. Bio-Inspired Comput.* **2020**, *15*, 254–283. [CrossRef]
58. Ramirez, A.; Romero, J.R.; Ventura, S. A survey of many objective optimisation in search-based software engineering. *J. Syst. Softw.* **2019**, *149*, 382–395. [CrossRef]
59. Lihong, H.; Nan, Y.; Jianhua, W.; Ying, S.; Kingking, D.; Ying, X. Application of mod-ified PSO in the optimization of reactive power. In Proceedings of the Chinese Control and Decision Conference, Guilin, China, 17–19 June 2009.
60. Prajapati, A. A particle swarm optimization approach for large-scale many-objective software architecture recovery. *J. King Saud Univ.—Comput. Inf. Sci.* **2022**, *34*, 8501–8513. [CrossRef]
61. Xia, Y.; Ikbal, M.A.; Shah, M.A. Construction design based on particle group optimization algorithm. *J. Intell. Syst.* **2021**, *30*, 1040–1053. [CrossRef]
62. Rao, X.; Yan, X. Particle Swarm Optimization Algorithm Based on Information Sharing in Industry 4.0. *Wirel. Commun. Mob. Comput.* **2022**, *2022*, 4328185. [CrossRef]
63. Rahman, A.F.A.; Selamat, H.; Ismail, F.S. Power Consumption Optimization of a Building Using Multiobjective Particle Swarm Optimization. *J. Teknol. (Sci. Eng.)* **2015**, *72*, 39–44. [CrossRef]
64. Zhang, X. Research on Building Energy Consumption Optimization Based on Improved Particle Swarm Optimization Algorithm. *J. Phys. Conf. Ser.* **2021**, *2037*, 012039. [CrossRef]
65. Kokare, M.B.; Tade, S.V. Application of artificial bee colony method for unit commitment. In Proceedings of the Fourth International Conference on Computing Communication Control and Automation, ICCUBEA, Pune, India, 16–18 August 2018.
66. Neagoe, V.; Neghina, C. An artificial bee colony approach for classification of re-mote sensing imagery. In Proceedings of the 10th International Conference on Electronics, Computers and Artificial Intelligence, ECAI, Iasi, Romania, 28–30 June 2018.
67. Karaboga, D.; Gorkemli, B.; Ozturk, C.; Karaboga, N. A comprehensive survey: Artificial bee colony (ABC) algorithm and applications. *Artif. Intell. Rev.* **2012**, *42*, 21–57. [CrossRef]
68. Karaboga, D.; Basturk, B. A powerful and efficient algorithm for numerical function optimization: Artificial bee colony (ABC) algorithm. *J. Glob. Optim.* **2007**, *39*, 459–471. [CrossRef]
69. Zhao, C.; Zhao, H.; Wang, G.; Chen, H. Improvement SVM classification performance of hyperspectral image using chaotic sequences in artificial bee colony. *IEEE Access* **2020**, *8*, 73947–73956. [CrossRef]
70. Wang, S.; Yang, J.; Liu, G.; Du, S.; Yan, J. Multi-objective path finding in stochastic networks using a biogeography-based optimization method. *Simulation* **2016**, *92*, 637–647. [CrossRef]
71. Sun, L.; Chen, T.; Zhang, Q. An artificial bee colony algorithm with random location updating. *Sci. Program.* **2018**, *2018*, 2767546. [CrossRef]
72. Cheng, L.; Yu, M.; Yang, J.; Wang, Y. An improved artificial bee colony algorithm based on beetle antennae search. In Proceedings of the Chinese Control Conference, Guangzhou, China, 27–30 July 2019.
73. Gao, H.; Shi, Y.; Pun, C.; Kwong, S. An improved artificial bee colony algorithm with its application. *IEEE Trans. Ind. Inform.* **2018**, *15*, 1853–1865. [CrossRef]
74. Chandra, M.; Niyogi, R. Web service selection using modified artificial bee colony algorithm. *IEEE Access* **2019**, *7*, 88673–88684. [CrossRef]
75. Zhang, S.; Liu, S. A discrete improved artificial bee colony algorithm for 0–1 knap-sack problem. *IEEE Access* **2019**, *7*, 104982–104991. [CrossRef]
76. Sulaiman, N.; Mohamad-Saleh, J. New Enhanced Artificial Bee Colony (JA-ABC5) Algorithm with Application for Reactive Power Optimization, Hindawi, Publishing Corporation. *Sci. World J.* **2015**, *2015*, 396189. [CrossRef] [PubMed]

77. Wang, C. Applied Artificial Bee Colony Optimization Algorithm in Fire Evacuation Routing System. *J. Appl. Math.* **2018**, *2018*, 7962952. [CrossRef]
78. Agarwal, D. *A Systematic Review on Artificial Bee Colony Optimization Technique*; International Science Press: Noida, India, 2016; Volume 9, pp. 5487–5500.
79. Hadidi, A. Structural optimization using artificial bee colony algorithm. In Proceedings of the 2nd International Conference on Engineering Optimization, Lisbon, Portugal, 6–9 September 2010.
80. Rezk, H.; Fathy, A.; Abdelaziz, A.Y. A comparison of different global MPPT techniques based on meta-heuristic algorithms for photovoltaic system subjected to partial shading conditions. *Renew. Sustain. Energy Rev.* **2017**, *74*, 377–386. [CrossRef]
81. Joshi, A.S.; Kulkarni, O.; Kakandikar, G.M.; Nandedkar, V.M. Cuckoo search optimization—A review. *Mater. Today Proc.* **2017**, *4*, 7262–7269. [CrossRef]
82. Wei, J.; Yu, Y. An effective hybrid cuckoo search algorithm for unknown parameters and time delays estimation of chaotic systems. *IEEE Access* **2017**, *6*, 6560–6571. [CrossRef]
83. Nugraha, D.A.; Lian, K. A novel MPPT method based on cuckoo search algorithm and golden section search algorithm for partially shaded PV system. In Proceedings of the IEEE Electrical Power and Energy Conference, EPEC, Toronto, ON, Canada, 10–11 October 2018.
84. Li, X.; Ma, S.; Yang, G. Synthesis of difference patterns for monopulse antennas by an improved cuckoo search algorithm. *IEEE Antennas Wirel. Propag. Lett.* **2016**, *16*, 141–144. [CrossRef]
85. Liu, L.; Liu, X.; Wang, N.; Zou, P. Modified cuckoo search algorithm with variational. *Algorithms* **2018**, *11*, 30. [CrossRef]
86. Aina, I.I. Olumuyiwa James Peter, Enhanced Cuckoo Intelligence Search Algorithm. *Int. J. Differ. Equ. (IJDE)* **2021**, *16*, 87–97.
87. Jasim, A.M.; Jasim, B.H.; Bureš, V. A novel grid-connected microgrid energy management system with optimal sizing using hybrid grey wolf and cuckoo search optimization algorithm. *Front. Energy Res.* **2022**, *10*, 960141. [CrossRef]
88. Wang, H.; Sheng, B.; Lu, Q.; Luo, R.; Fu, G. A multiobjective cuckoo search algorithm based on the record matrix for a mixed-model assembly line car-sequencing problem. *IEEE Access* **2020**, *8*, 76453–76470. [CrossRef]
89. Xiong, Y. Cuckoo search algorithm based on cloud model and its application. *Sci. Rep.* **2023**, *13*, 10098. [CrossRef]
90. Al-Abaji, M.A. Cuckoo Search Algorithm: Review and its Application. *Tikrit J. Pure Sci.* **2021**, *26*, 137–144. [CrossRef]
91. Aslam, S. Towards Efficient Energy Management of Smart Buildings Exploiting Heuristic Optimization with Real Time and Critical Peak Pricing Schemes. *Energies* **2017**, *10*, 2065. [CrossRef]
92. Senthilnath, J.; Kulkarni, S.; Benediktsson, J.A.; Yang, X.S. A novel approach for multispectral satellite image classification based on the bat algorithm. *IEEE Geosci. Remote Sens. Lett.* **2016**, *13*, 599–603. [CrossRef]
93. Zhu, L.F.; Wang, J.S.; Guo, S.S.; Guo, M.W.; Xie, W. Data clustering method based on improved bat algorithm with six convergence factors and local search operators. *IEEE Access* **2020**, *8*, 80536–80560. [CrossRef]
94. Chen, G.; Qian, G.; Zhang, Z.; Sun, Z. Applications of novel hybrid bat algorithm with constrained Pareto fuzzy dominant rule on multi-objective optimal power flow problems. *IEEE Access* **2019**, *7*, 52060–52084. [CrossRef]
95. Rugema, F.X.; Yan, G.; Mugemanyi, S.; Jia, Q.; Zhang, S.; Bananeza, C. A Cauchy-Gaussian quantum-behaved bat algorithm applied to solve the economic load dispatch problem. *IEEE Access* **2020**, *9*, 3207–3228. [CrossRef]
96. Yu, S.; Yu, Y.; Zhang, M.; Wu, E.; Wu, L. The economic benefit of liner ships. *Adv. Mech. Eng.* **2017**, *9*, 1–11. [CrossRef]
97. Advantages and Disadvantages of Bat Algorithm. Available online: https://www.bartleby.com/essay/Advantages-And-Disadvantages-Of-Bat-Algorithm-FJ7QTTVY3G (accessed on 7 November 2023).
98. Presetnik, P. Bats in Buildings of Cultural Heritage of the Republic of Slovenia. 2021. Available online: https://www.researchgate.net/publication/351625096 (accessed on 30 October 2023).
99. Fayaz, M. Energy Consumption Optimization and User Comfort Management in Residential Buildings Using a Bat Algorithm and Fuzzy Logic. *Energies* **2018**, *11*, 161. [CrossRef]
100. Hanah, A. Reduction of Cooling Energy Needs for Buildings. *J. Eng. Res. (ERJ)* **2022**, *6*, 25–27.
101. Perera, A.T.D. Enhancing flexibility for climate change using seasonal energy storage (aquifer thermal energy storage) in distributed energy systems. *Appl. Energy* **2023**, *340*, 120957. [CrossRef]
102. Yan, Z.; Zhang, J.; Zeng, J.; Tang, J. Nature-inspired approach: An enhanced whale optimization algorithm for global optimization. *Math. Comput. Simul.* **2021**, *185*, 17–46. [CrossRef]
103. Jagatheesan, K.; Anand, B.; Samantha, S.; Dey, N.; Ashour, A.S.; Balas, V.E. Design of a proportional integral derivative controller foran automatic generation control of multi-area power thermal system using firefly algorithm. *IEEE/CAA J. Autom. Sin.* **2019**, *6*, 503–515. [CrossRef]
104. Alb, M.; Alotto, P.; Magele, C.; Renhart, W.; Preis, K.; Trapp, B. Firefly algorithm for finding optimal shapes of electromagnetic devices. *IEEE Trans. Magn.* **2015**, *52*, 1–4. [CrossRef]
105. Liaquat, S.; Fakhar, M.S.; Kashif, S.A.R.; Rasool, A.; Saleem, O. Application of dy-namically search space squeezed modified firefly algorithm to a novel short term economic dispatch of multi-generation systems. *IEEE Access* **2020**, *9*, 1918–1939. [CrossRef]
106. Wang, C.; Chu, X. An improved firefly algorithm with specific probability and its engineering application. *IEEE Access* **2019**, *7*, 57424–57439. [CrossRef]
107. Aydelik, I.B. A hybrid firefly and particle swarm optimization algorithm for com-putationally expensive numerical problems. *Appl. Soft Comput.* **2018**. [CrossRef]

108. Sarangi, S.K.; Panda, R.; Saranga, A. Design of adaptive IIR filter with modified firefly algorithm for parameter estimation. In Proceedings of the Technologies for Smart-City Energy Security and Power, ICSESP, Bhubaneswar, India, 28–30 March 2018.
109. Sarangi, S.K.; Panda, R.; Priyadarshni, S.; Sarangi, A. A new modified firefly algorithm for function optimization. In Proceedings of the International Conference on Electrical, Electronics, and Optimization Techniques, ICEEOT, Chennai, India, 3–5 March 2016.
110. Mortazavi, A. Comparison of Metaheuristic Techniques Performance on Minimizing the Total Heating Cost of Residential Buildings. In Proceedings of the IES'21 International Engineering Symposium, Engineering Applications in Industry, Izmir, Turkey, 13–18 December 2021.
111. Wahid, F.; Fayaz, M.; Aljarbouh, A.; Mir, M.; Aamir, M.; Imran. Energy Consumption Optimization and User Comfort Maximization in Smart Buildings Using a Hybrid of the Firefly and Genetic Algorithms. *Energies* **2020**, *13*, 4363. [CrossRef]
112. Dounis, A.I.; Caraiscos, C. Advanced Control Systems Engineering for Energy and Comfort Management in a Building Environment—A Review. *Renew. Sustain. Energy Rev.* **2009**, *13*, 1246–1261. [CrossRef]
113. Moayedi, H.; Mosavi, A. Suggesting a Stochastic Fractal Search Paradigm in Combination with Artificial Neural Network for Early Prediction of Cooling Load in Residential Buildings. *Energies* **2021**, *14*, 1649. [CrossRef]
114. Liao, Y.; Liu, Y.; Chen, C.; Zhang, L. Green Building Energy Cost Optimization with Deep Belief Network and Firefly Algorithm. *Front. Energy Res.* **2021**, *9*, 805206. [CrossRef]
115. Kulkarni, V.R.; Desai, V. ABC and PSO: A comparative analysis. In Proceedings of the IEEE International Conference on Computational Intelligence and Computing Research, Chennai, India, 15–17 December 2016.
116. Tanveer, M.S.R.; Islam, M.J.; Akhand, M.A.H. A comparative study on prominent swarm intelligence methods for function optimization. *Glob. J. Technol. Optim.* **2016**, *7*, 203. [CrossRef]
117. Alsariera, Y.A.; Alamri, H.S.; Nasser, A.M.; Majid, M.A.; Zamli, K.Z. Comparative performance analysis of bat algorithm and bacterial foraging optimization algorithm using standard benchmark functions. In Proceedings of the Malaysian Software Engineering Conference, Langkawi, Malaysia, 23–24 September 2014.
118. Attia, S.; Gratia, E.; De Herde, A.; Hensen, J. *Building Performance Simulation for Design and Operation*; Routledge: London, UK, 2013.
119. Spitler, J.D.; Cremaschi, L. *Ground-Source Heat Pumps: Fundamentals, Experiments, and Applications*; Wiley: Hoboken, NJ, USA, 2019.
120. Cengel, Y.A.; Turner, R.H. *Fundamentals of Thermal-Fluid Sciences*; McGraw-Hill Education: New York, NY, USA, 2015.
121. Szokolay, S.V. *Introduction to Architectural Science: The Basis of Sustainable Design*; Elsevier: Amsterdam, The Netherlands, 2004.
122. Duffie, J.A.; Beckman, W.A. *Solar Engineering of Thermal Processes*; Wiley: Hoboken, NJ, USA, 2013.
123. Hirsch, H. Integrated Building Automation and Lighting Control: Modern Lighting Systems and Control for Commercial. In *Industrial, and Residential Buildings*; CRC Press: Boca Raton, FL, USA, 2012.
124. U.S. Green Building Council. *LEED v4 for Building Design and Construction*; U.S. Green Building Council: Washington, DC, USA, 2013.
125. BREEAM. *BREEAM International New Construction 2016 Technical Manual*; Building Research Establishment: Watford, UK, 2018.
126. Albogamy, F.R.; Khan, S.A.; Hafeez, G.; Murawwat, S.; Khan, S.; Haider, S.I.; Basit, A.; Thoben, K.-D. Real-Time Energy Management and Load Scheduling with Renewable Energy Integration in Smart Grid. *Sustainability* **2022**, *14*, 1792. [CrossRef]
127. Cai, Y.; Teunter, R.H.; de Jonge, B. A data-driven approach for condition-based maintenance optimization. *Eur. J. Oper. Res.* **2023**, *311*, 730–738. [CrossRef]

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